Using Machine Learning methods for detection abnormality in lower back pain

Lower Back Pain Symptoms Dataset

by: Mohamed Radwan

Agenda

- Understand the data
- Discuss different machine learning methods for classifications
- Provide interpretations for the predictions of the machine learning methods

Lower Back Pain

- “Low back pain can result from many different injuries, conditions or diseases most often, an injury to muscles or tendons in the back” Source:clevelandclinic.org
- Norwegian national statistics show that musculoskeletal disorders are the most common cause for sick leave, disability retirement and for attending primary care. Source: Jonas M. Kinge, 2014
- Low back pain and neck pain are leading causes of Disability Adjusted Life Years (DALYs) in Norway. Source: Jonas M. Kinge, 2014

Objective of the task

- Binary classification of each data sample into normal/abnormal

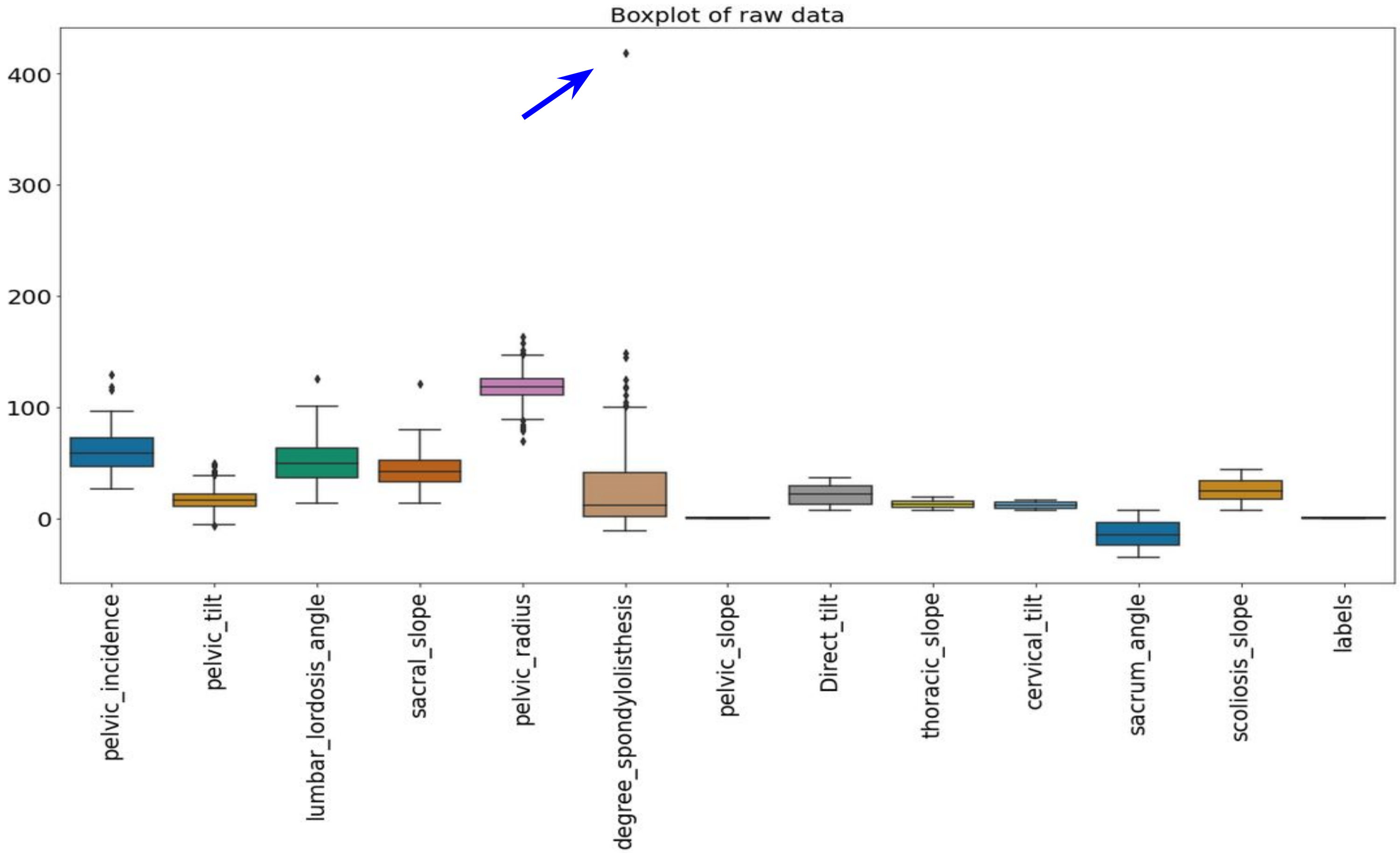
- Providing an interpretation of the classification predictions results for the best model, So we can have an idea how the model makes predictions.

Exploring Data

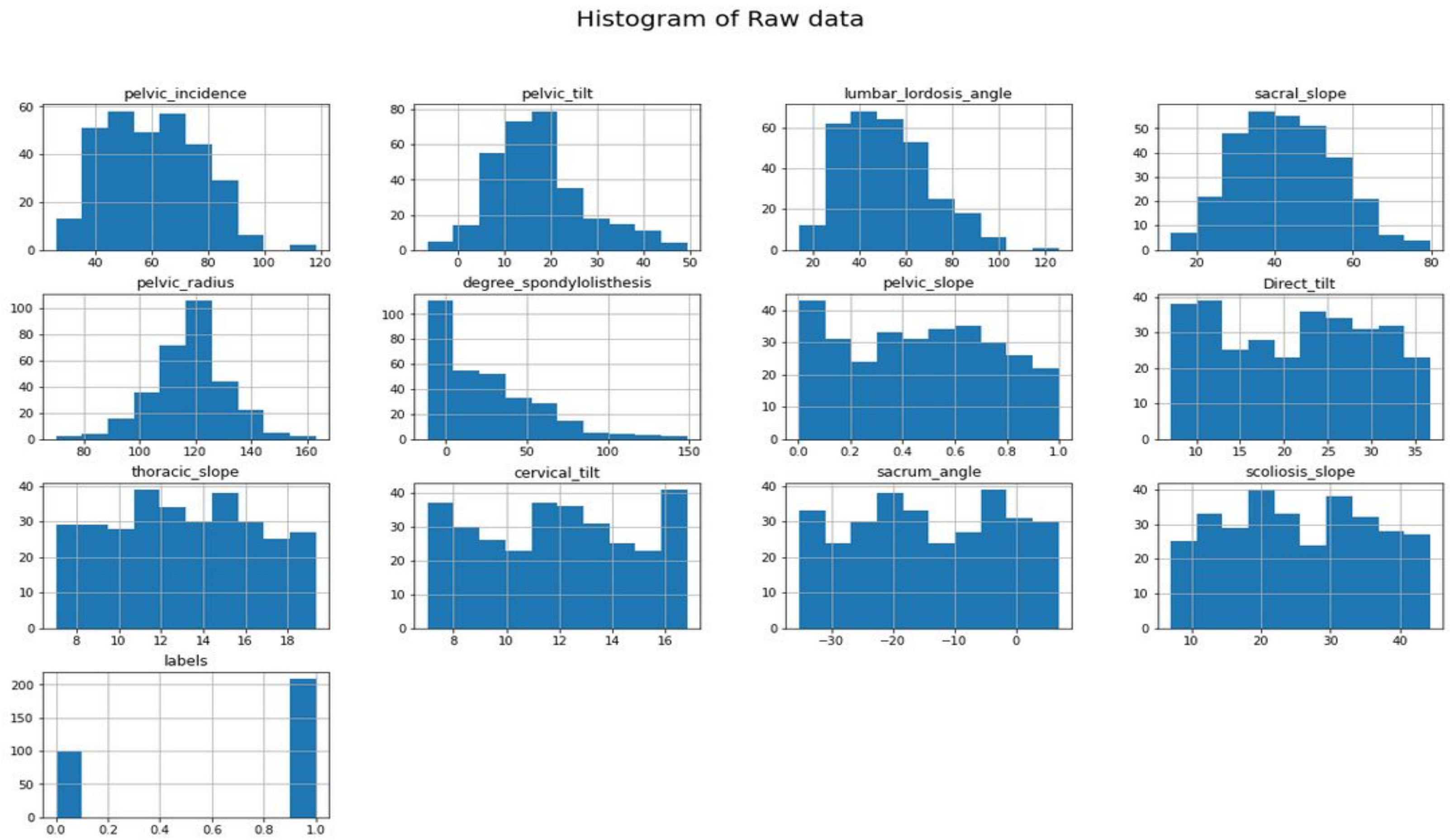
- 310 data samples
- 12 numeric features, 1 Binary Class Attribute (normal/abnormal)

	pelvic_incidence	pelvic_tilt	lumbar_lordosis_angle	sacral_slope	pelvic_radius	degree_spondylolisthesis	....	labels
count	310.000000	310.000000	310.000000	310.000000	310.000000	310.000000		310.000000
mean	60.496653	17.542822	51.930930	42.953831	117.920655	26.296694		0.677419
std	17.236520	10.008330	18.554064	13.423102	13.317377	37.559027		0.468220
min	26.147921	-6.554948	14.000000	13.366931	70.082575	-11.058179		0.000000
25%	46.430294	10.667069	37.000000	33.347122	110.709196	1.603727		0.000000
50%	58.691038	16.357689	49.562398	42.404912	118.268178	11.767934		1.000000
75%	72.877696	22.120395	63.000000	52.695888	125.467674	41.287352		1.000000
max	129.834041	49.431864	125.742385	121.429566	163.071041	$\boxed{418.543082}$		1.000000

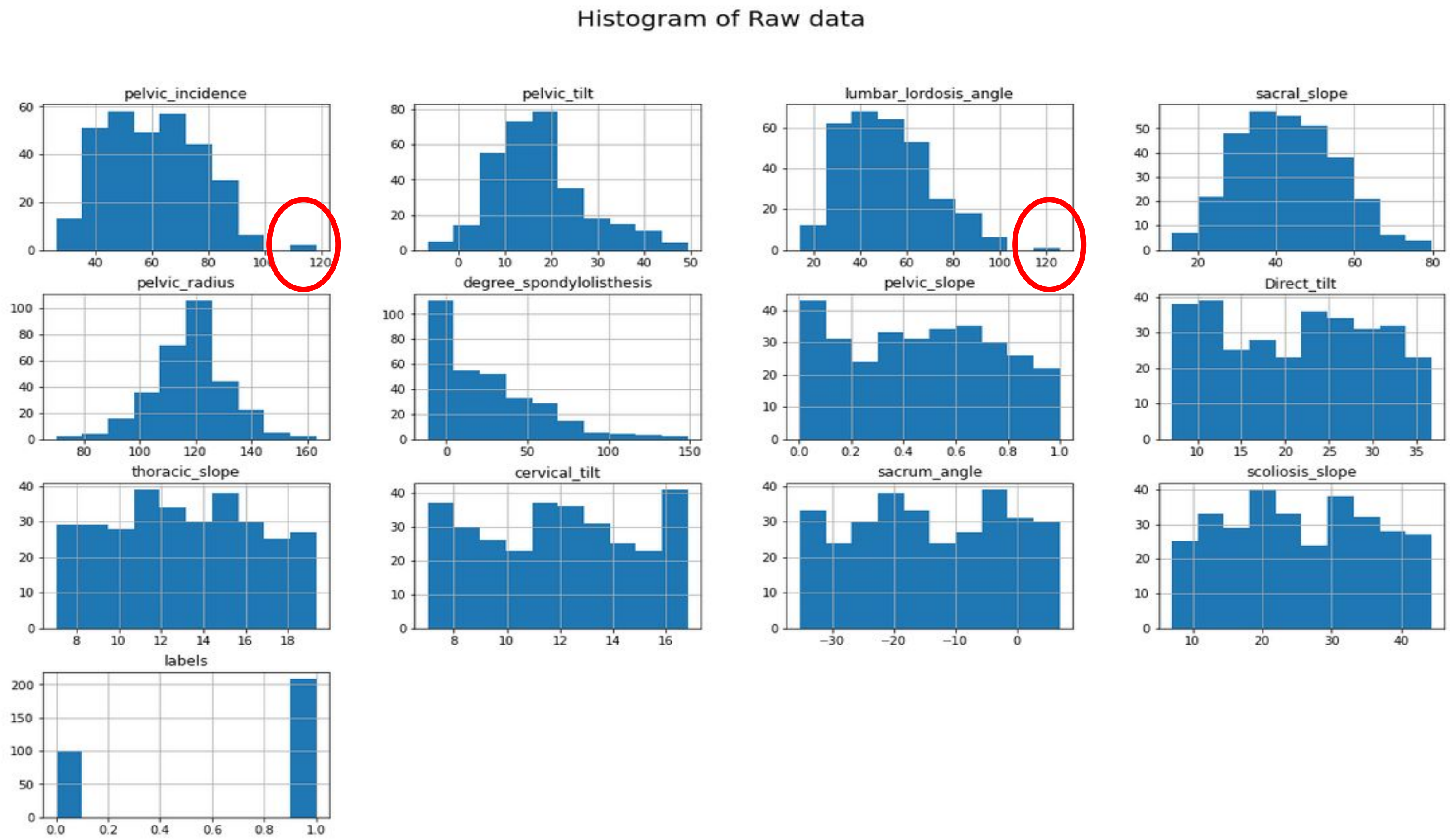
Exploring Data



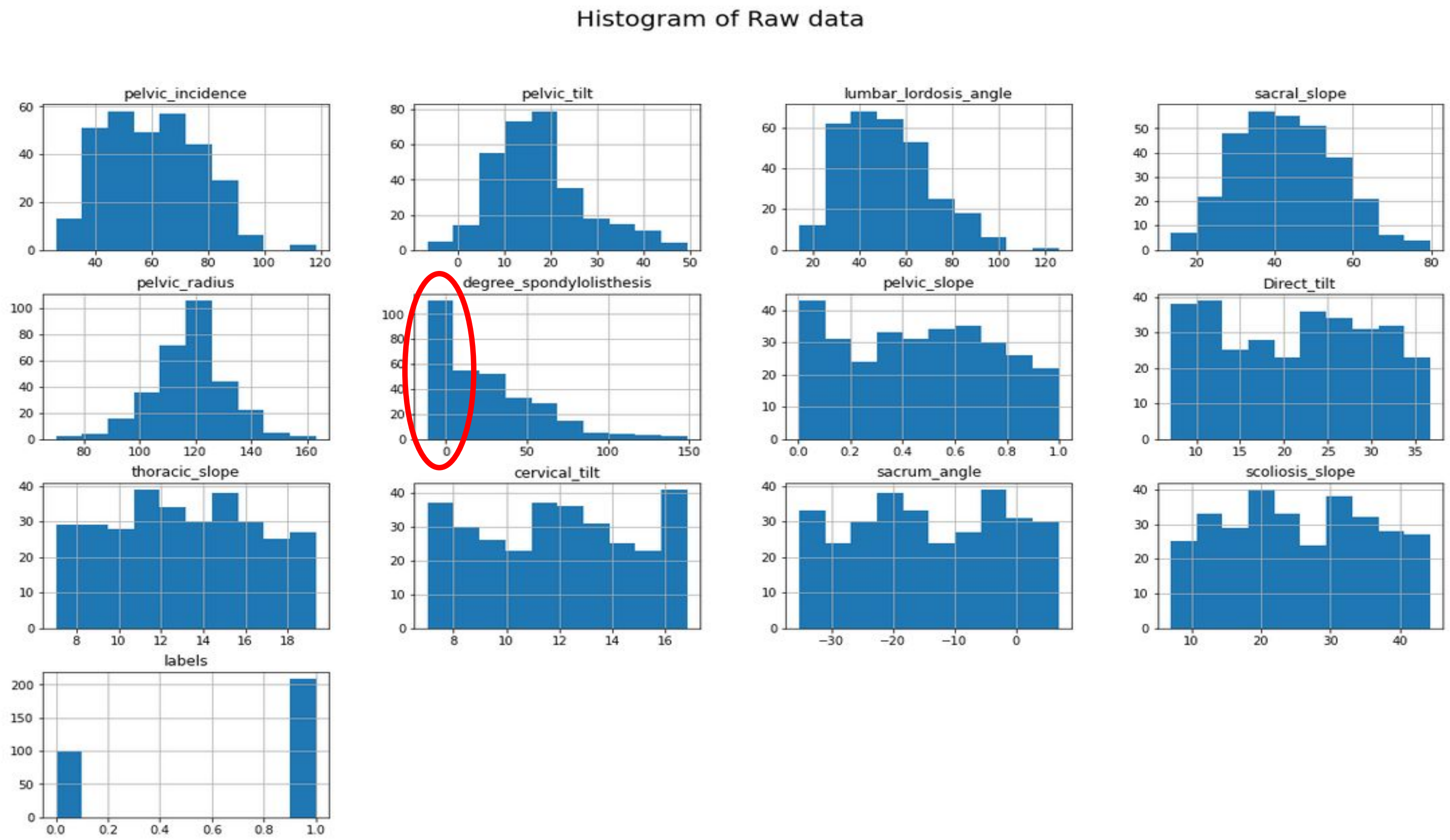
Exploring Data



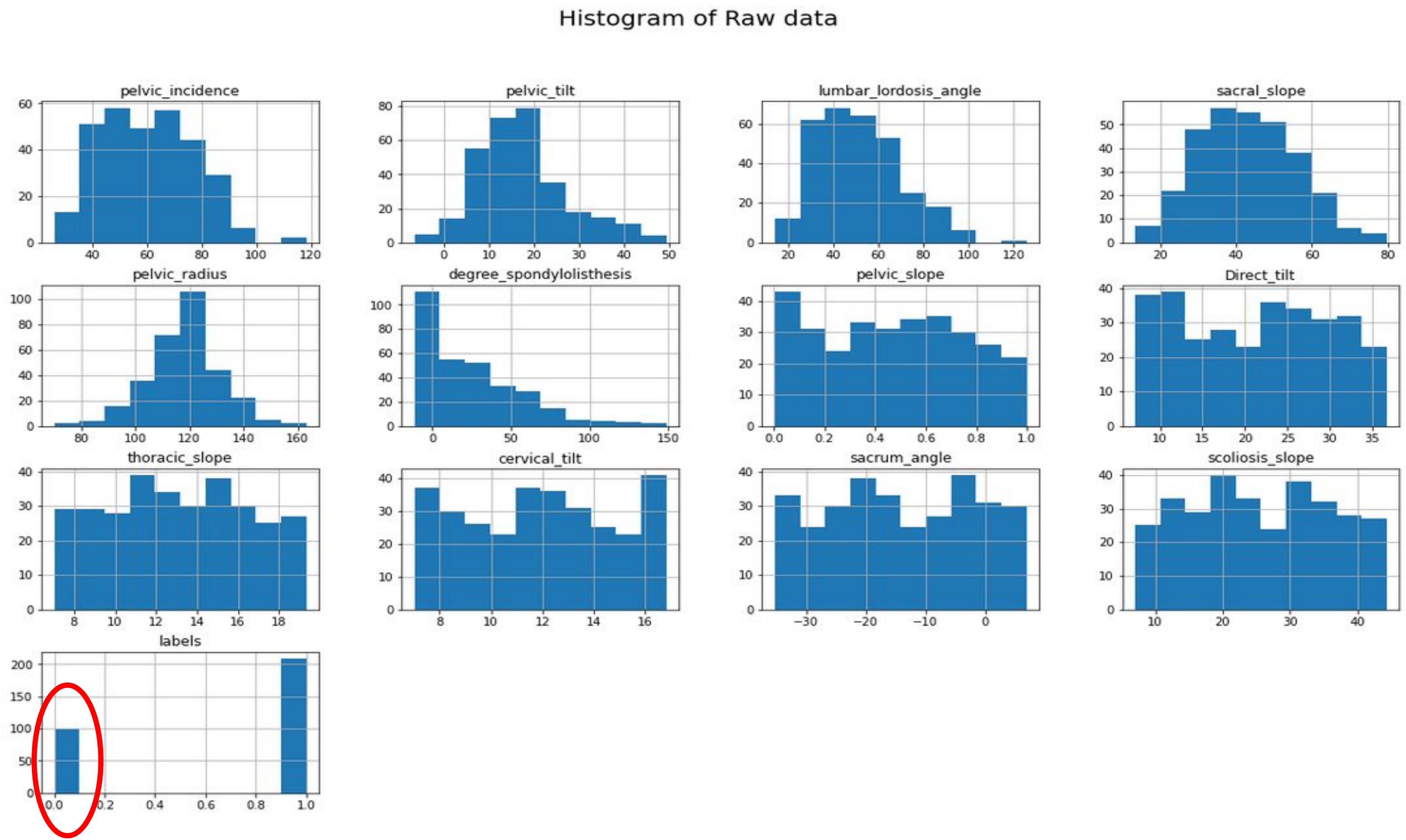
Exploring Data



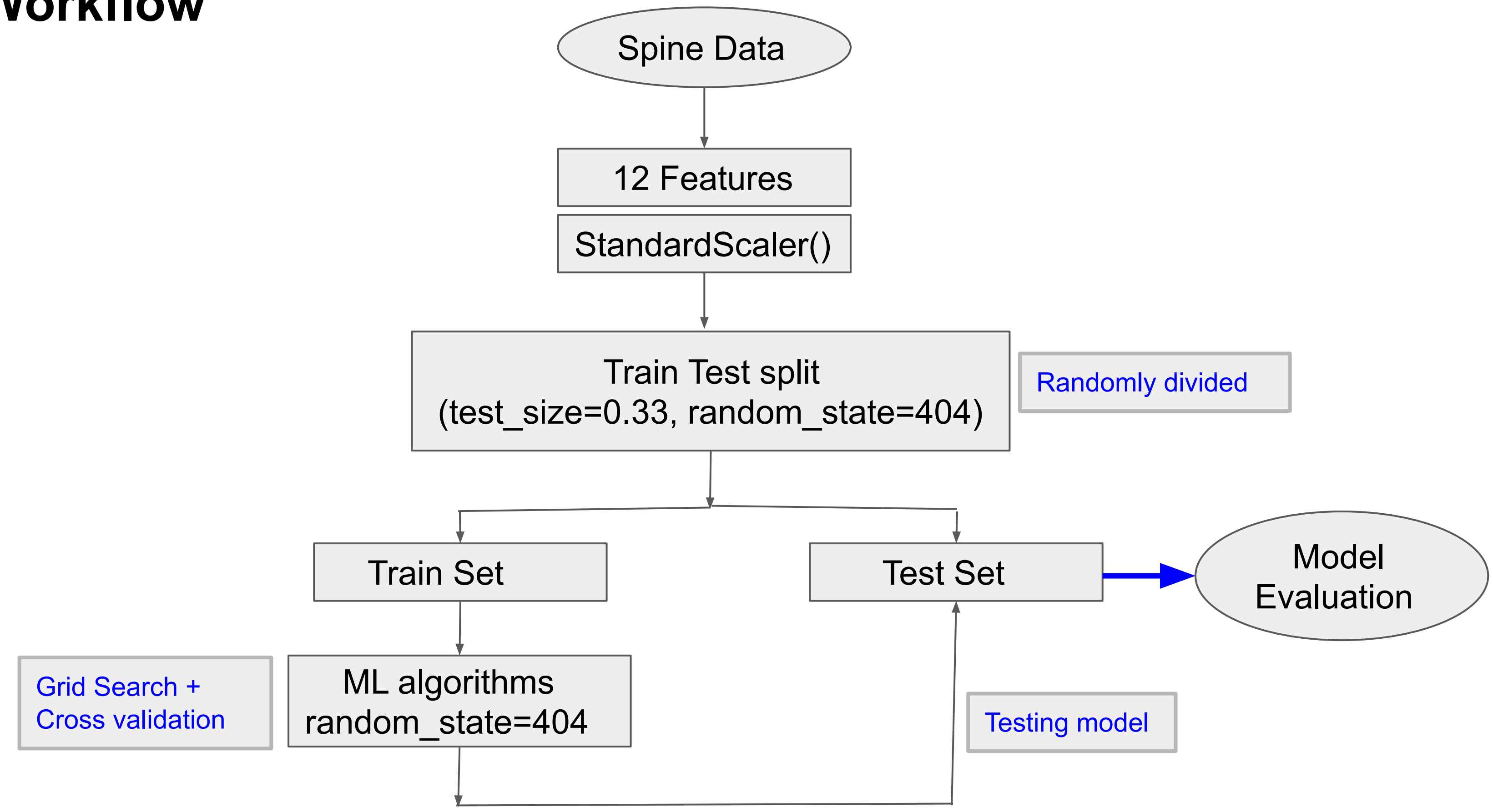
Exploring Data



Exploring Data



Workflow

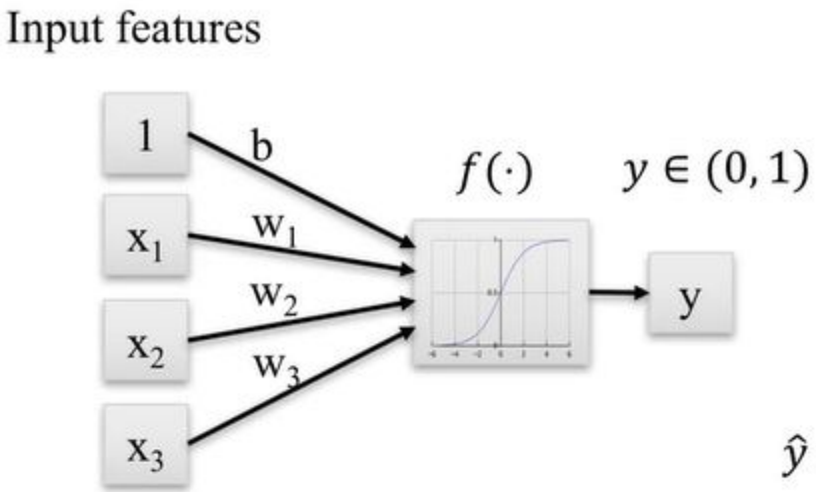


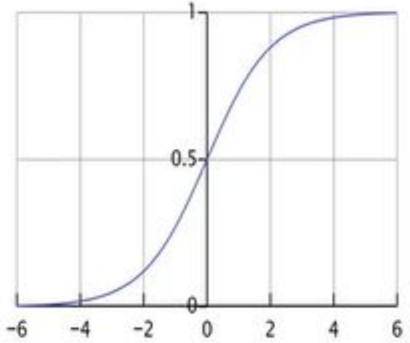
Modified after:[M. Raihan-Al-Masud, M. Rubaiyat, 2020]

Used Machine Learning algorithms

- Logistic Regression
- Support Vector Machine
- Decision Tree
- Random Forest
- Artificial Neural Network

Logistic Regression



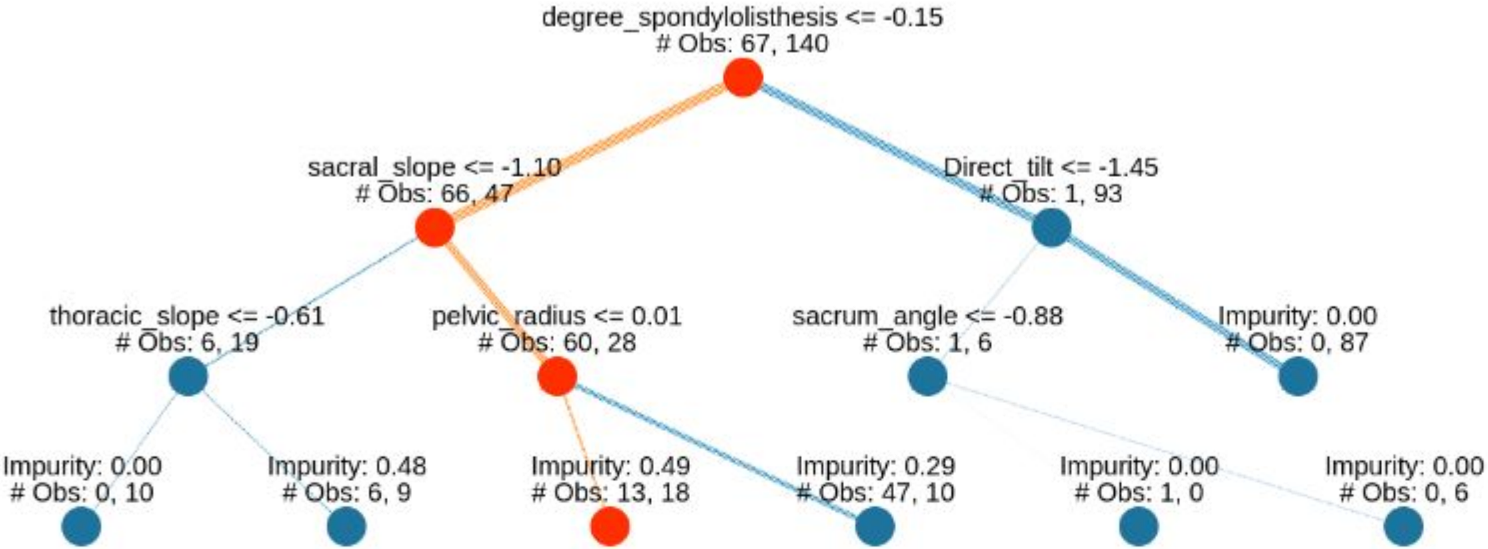


$$\hat{y} = \text{logistic}(\hat{b} + \hat{w}_1 \cdot x_1 + \cdots \hat{w}_n \cdot x_n)$$

$$= \frac{1}{1 + \exp\left[-(\hat{b} + \hat{w}_1 \cdot x_1 + \cdots \hat{w}_n \cdot x_n)\right]}$$

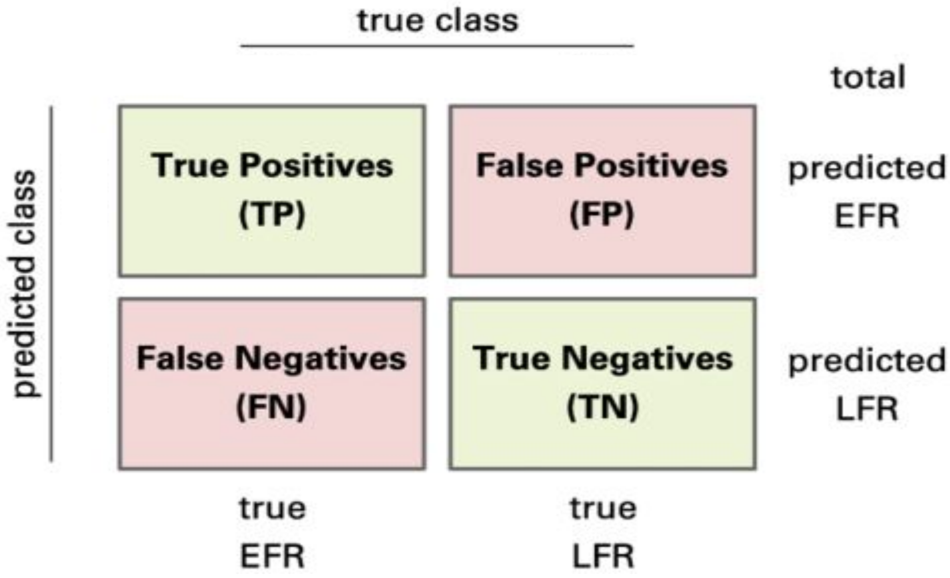
Source: http://luisevalencia.com

Decision Tree



Evaluation Metrics

- Maximize TP and TN. Minimize FN or maximize Recall



$$PR = \frac{TP}{TP+FP}$$

$$RE = \frac{TP}{TP+FN}$$

$$CA = \frac{TP+TN}{TP+TN+FP+FN}$$

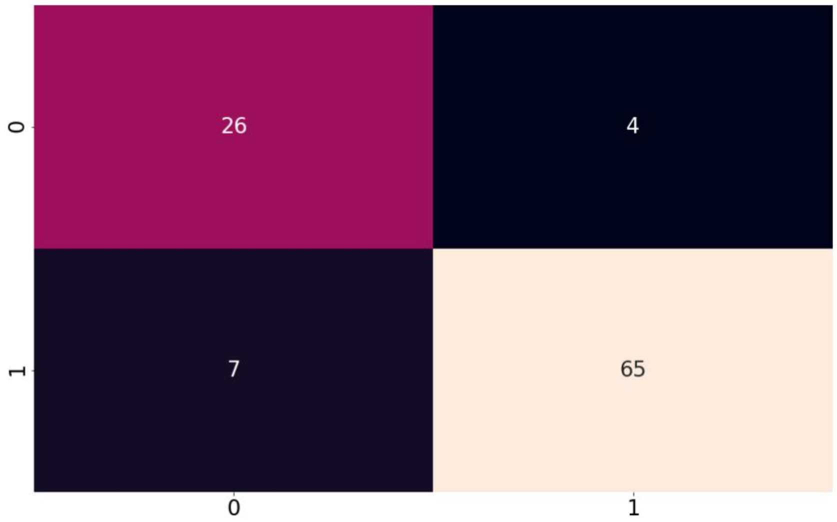
$$F_1 = \frac{2TP}{2TP+FP+FN}$$

Source: Sebastian Bittrich, etal., 2019

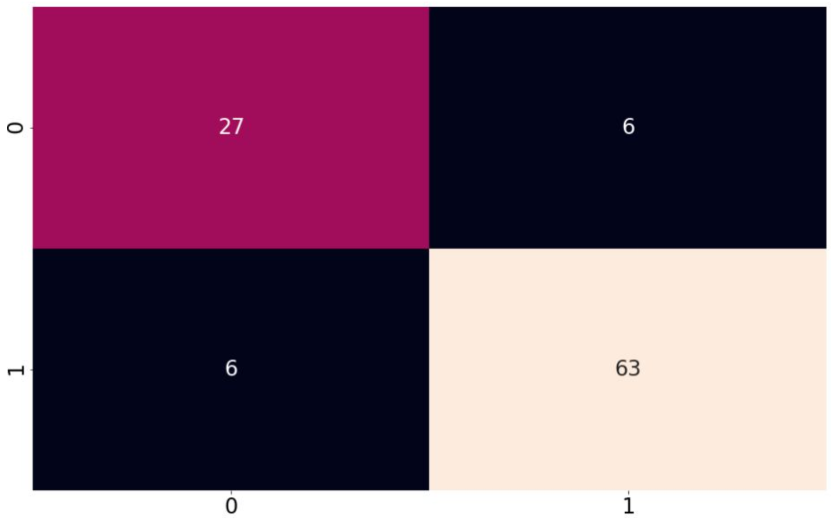
Results

Model	Accuracy	F1	Precision	Recall
Logistic Regression	0.863	0.841	0.847	0.835
Random Forest	**0.892**	**0.874**	**0.885**	**0.865**
Decision Tree	0.775	0.744	0.743	0.746
Support Vector Machine	0.863	0.841	0.847	0.835
Multilayer Perceptron	0.882	0.866	0.865	0.866

Confusion matrix (Random Forest vs Neural Network)

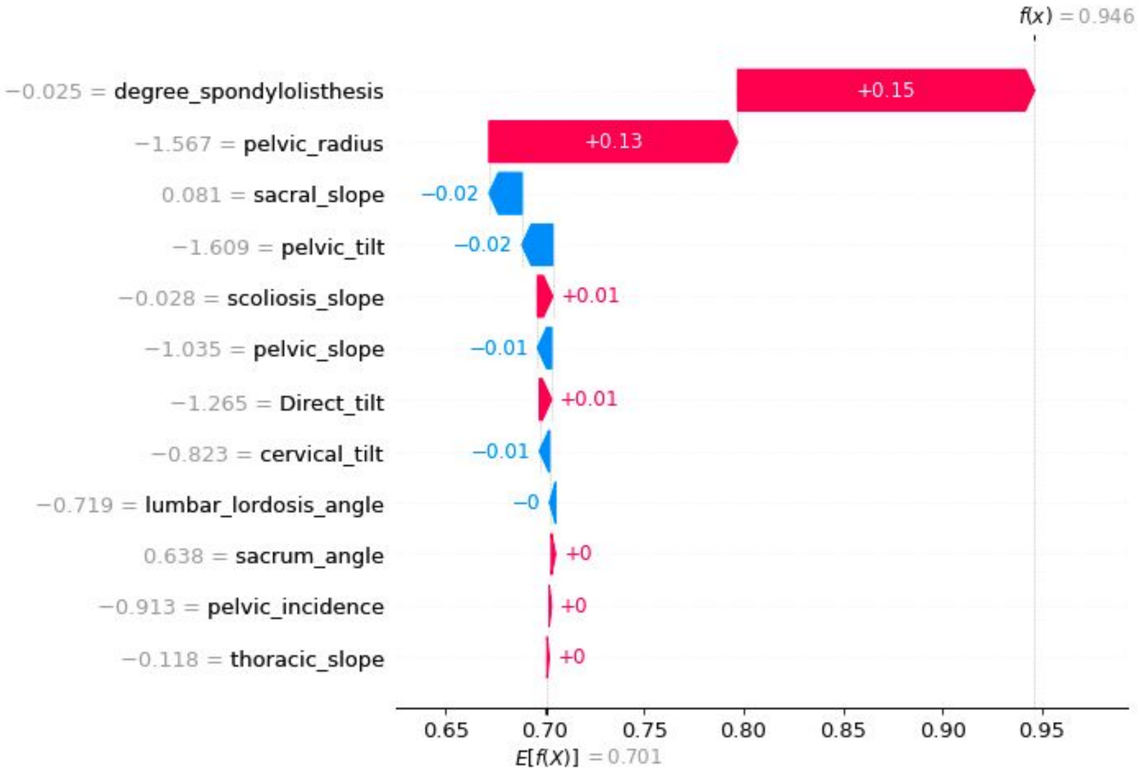


Random Forest

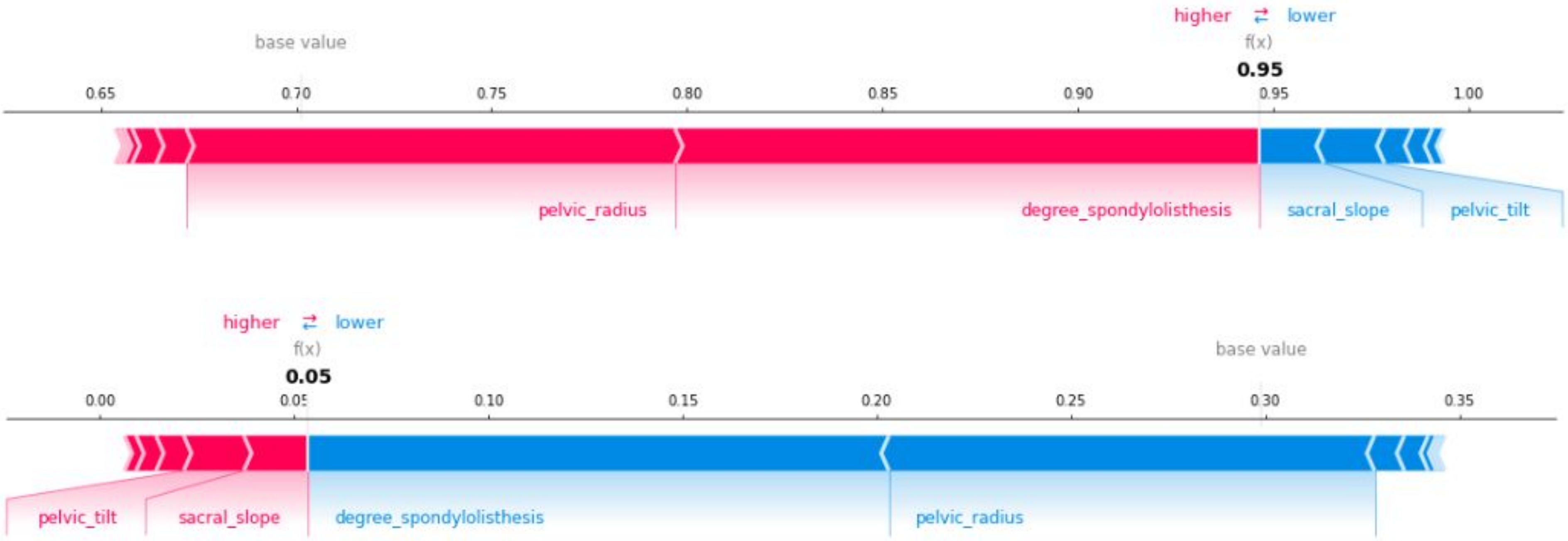


Neural Network

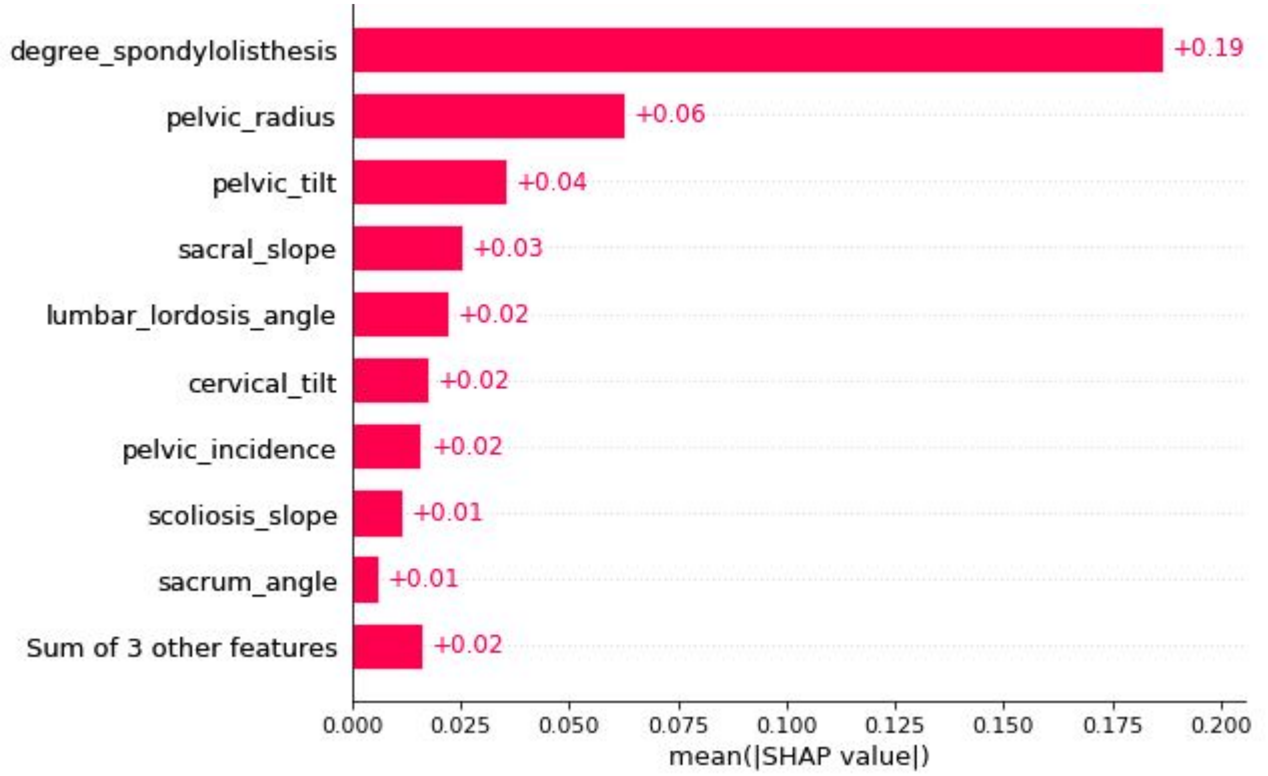
Random Forest Interpretation (Waterfall plot of first sample)



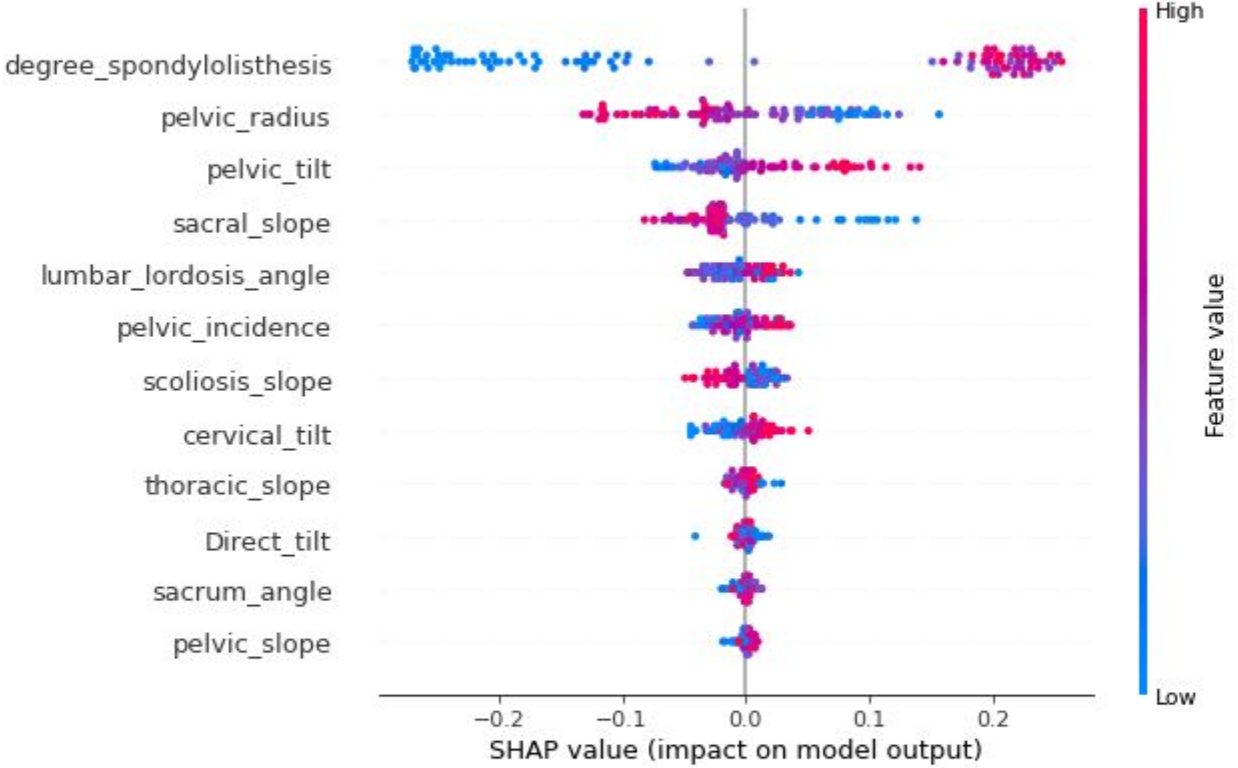
Random Forest Interpretation (normal vs abnormal interpretation)



Random Forest Interpretation



Random Forest Interpretation (beeswarm of the whole dataset)



Conclusions

- Logistic regression achieved competitive results
- Decision Tree was unstable in performance
- Random Forest achieved highest performances followed by neural networks
- Making more complicated models leads to overfitting that hurts accuracy
- Methods and results: https://github.com/mhmdrdwn/spine

Questions