Predicting Spinal Condition using various biomechanical attributes of the pelvic and lumbar spine

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Introduction

- Machine learning applications in exploratory orthopedic medicine research
- Random forest applications in spine research
- Support Vector Machine model usage in an orthopedic context.

Introduction: Spondylolisthesis and disk herniation

- Spondylolisthesis is a unilateral or bilateral defect (fracture or separation) in the vertebral pars interarticularis, usually in the lower lumbar vertebrae
- Symptoms: pain that spreads across the patient's lumbar region and radiates into posterior legs
- Disk Herniation is when the soft center of a spinal disk pushes into a crack in the tougher exterior casing
- Symptoms: Lower back pain (chronic)
- Both are often misdiagnosed

Introduction: Purpose of this study

- Accurately categorize spinal osteoarthritis conditions into the categories: normal, disk herniation, and spondylolisthesis based on biomechanical attributes of the shape and orientation of the pelvis and lumbar spine.
- Compare the accuracy of categorizations between support vector machine models and a random forest model
- An accurate machine learning algorithm could serve as an assistance tool for physicians to consult while considering a diagnosis, with the hopes of reducing misdiagnosis

Methods: The Data

- These data were obtained from a selection of three-hundred sixty patients during the medical residence period of Dr. Henrique da Mota, in the Group of Applied Research in Orthopedics (GARO), at the Centre Medico-Chirurgical de Réadaptation des Massues in Lyon, France
- 360 Patients: volunteers that were asymptomatic for disk herniation and Spondylolisthesis
- Spinal condition categorizations: Normal, Disk Hernia, and Spondylolisthesis

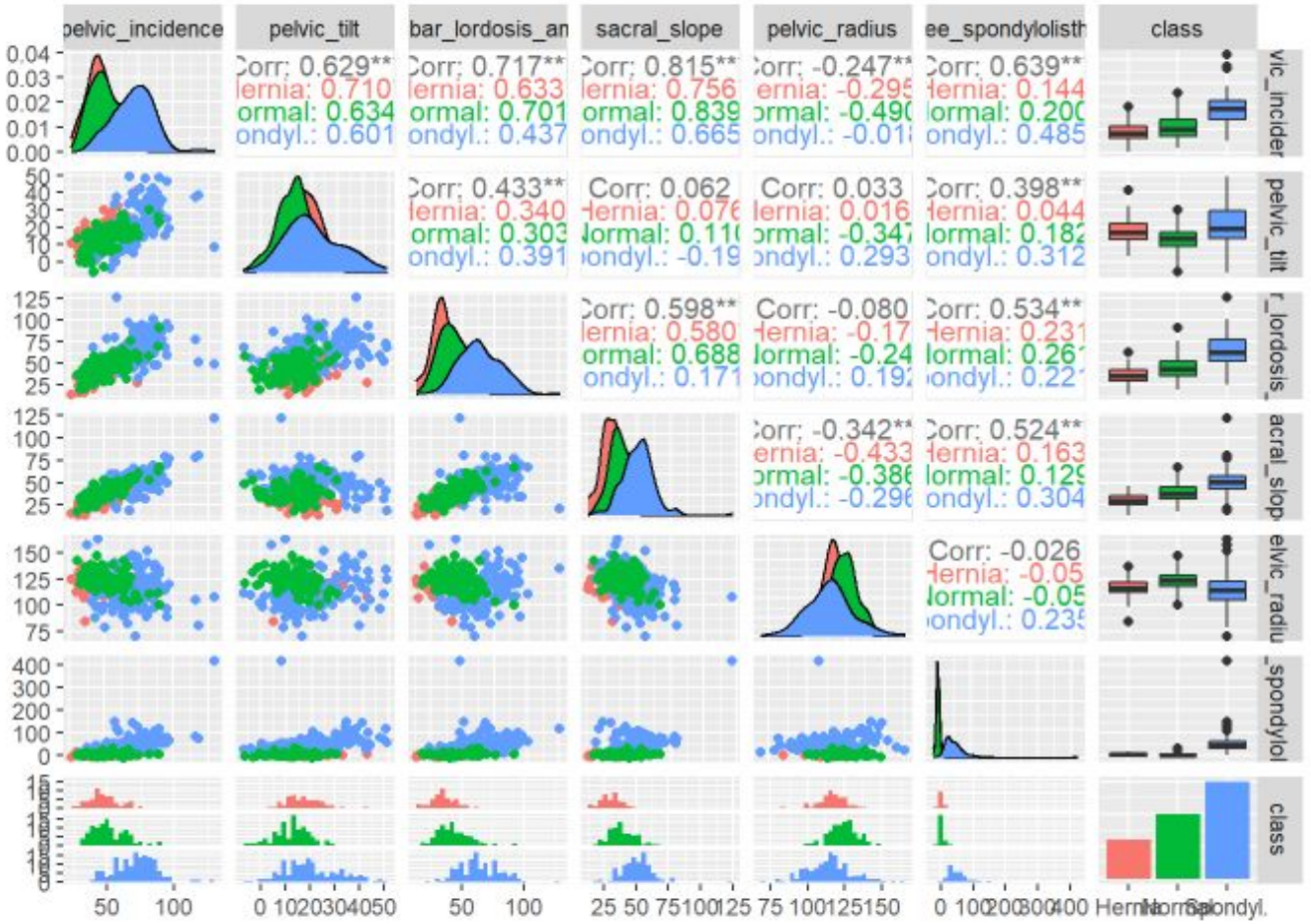
Methods: The predictors

- Six Predictors
  - Pelvic Incidence
  - Pelvic Tilt
  - Lumbar Lordosis Angle
  - Sacral Slope
  - Pelvic Radius
  - Grade of Spondylolisthesis

Characteristic	N	Hernia, N = 60[1]	Normal, N = 100[1]	Spondylolisthesis, N = 150[1]	p-value[2]
pelvic_incidence	310	48 (11)	52 (12)	72 (15)	<0.001
pelvic_tilt	310	17 (7)	13 (7)	21 (12)	<0.001
lumbar_lordosis_angle	310	35 (10)	44 (12)	64 (16)	<0.001
sacral_slope	310	30 (8)	39 (10)	51 (12)	<0.001
pelvic_radius	310	116 (9)	124 (9)	115 (16)	<0.001
degree_spondylolisthesis	310	2 (6)	2 (6)	52 (40)	<0.001

[1]Mean (SD)

[2]One-way ANOVA


pelvic_incidence
pelvic_tilt
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class
Corr: 0.629**
lernia: 0.710
ormal: 0.634
ondyl.: 0.601
Corr: 0.717**
lernia: 0.633
ormal: 0.701
ondyl.: 0.437
Corr: 0.815**
lernia: 0.756
ormal: 0.839
ondyl.: 0.665
Corr: -0.247**
ernia: -0.295
ormal: -0.490
ondyl.: -0.01
Corr: 0.639**
lernia: 0.144
lormal: 0.200
ondyl.: 0.485
Corr: 0.433**
lernia: 0.340
ormal: 0.303
ondyl.: 0.391
Corr: 0.062
Hernia: 0.076
Normal: 0.11
ondyl.: -0.19
Corr: 0.033
lernia: 0.016
ormal: -0.347
ondyl.: 0.293
Corr: 0.398**
lernia: 0.044
lormal: 0.182
ondyl.: 0.312
Corr: 0.598**
lernia: 0.580
ormal: 0.688
ondyl.: 0.171
Corr: -0.080
Hernia: -0.17
lormal: -0.24
ondyl.: 0.192
Corr: 0.534**
lernia: 0.231
lormal: 0.26
ondyl.: 0.22
Corr: -0.342**
ernia: -0.433
ormal: -0.386
ondyl.: -0.296
Corr: 0.524**
lernia: 0.163
lormal: 0.129
ondyl.: 0.304
Corr: -0.026
Hernia: -0.05
Normal: -0.05
ondyl.: 0.235
vic_incider
pelvic_tilt
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class
Hernia
Normal
Spondyl.

Methods: Modeling and Algorithms

- Compare a Random Forest and Support Vector Machine Model
- Random Forest model
  - 5-fold cross-validation used to train / test the algorithm and obtain CV errors and standard errors
  - Grid search to select the best parameter values (trees: 50, 250, 500 / predictors: 2, 3, 6)
  - The best parameters for a given training set were selected using out-of-bag MSE
- Support Vector Machine models
  - 5-fold cross-validation used to train / test the algorithm and obtain CV errors and standard errors
  - One model trained with a linear kernel; one model trained with a radial basis kernel
  - Grid of parameters were tested (epsilon: 0, 0.25, 0.50, 0.075, 1.00 / cost: 1-5)
- We wanted to find the best predictive model between these two approaches

Results: Overall Performance

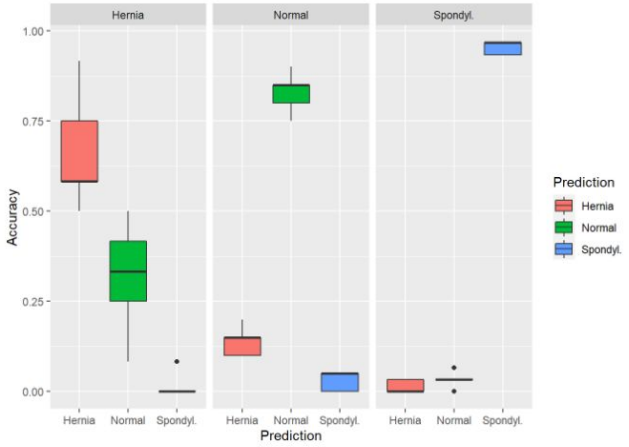
	Hernia	Normal	Spondylolisthesis
SVM (Linear)	0.333(0.167)	0.170(0.057)	0.047(0.018)
SVM (RBF)	0.283(0.095)	0.180(0.110)	0.060(0.037)
Random Forest	0.433(0.199)	0.230(0.104)	0.040(0.043)

(1) Error (Standard Error)

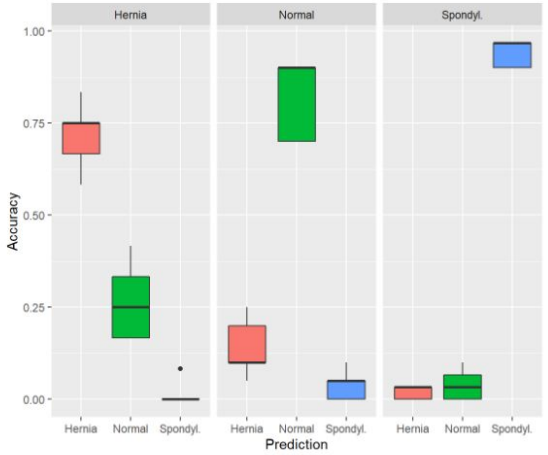
Results: AUC (Hand and Till)

	AUC
SVM (Linear)	0.952
SVM (RBF)	0.944
Random Forest	0.923

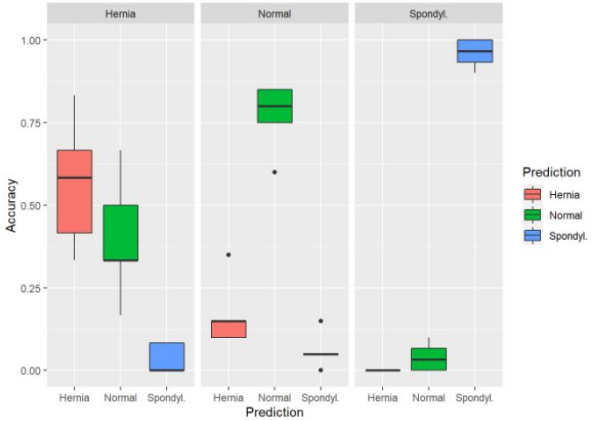
SVM (Linear)



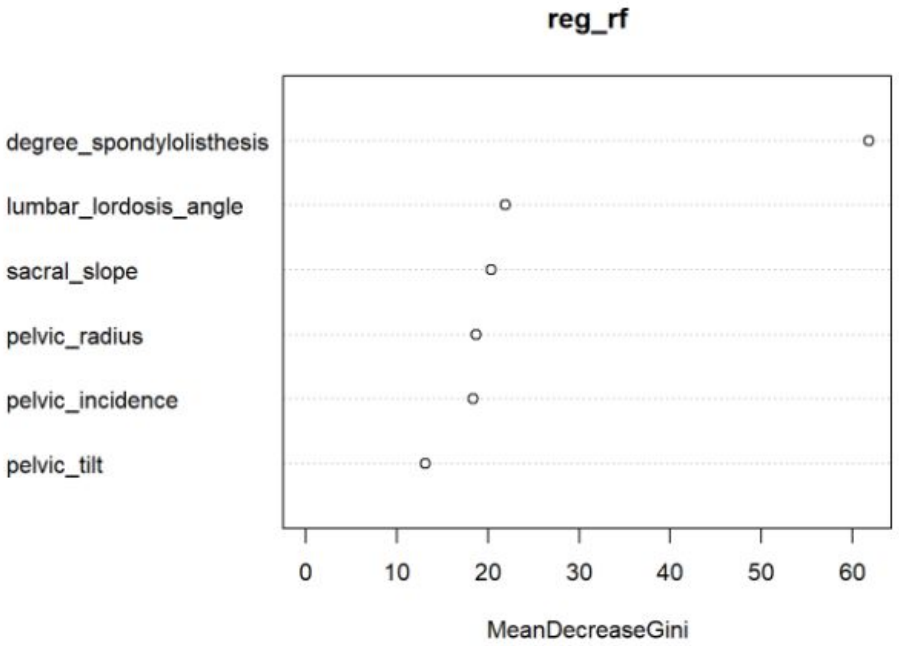
SVM (RBF)



Random Forest



Results: Gini importance



Discussion

- Our results indicate SVM-linear, SVM-RBF, and RF, show very promising performance.
    - Models differ in precision
- All three algorithms performed the best in terms of prediction accuracy on the spondylolisthesis condition, second on the normal condition, and the lowest on the disk hernia condition.
    - 60% accuracy across all three algorithms, despite disk hernia being low.
- An explanation for low prediction accuracy for disk herniation
- Overall promising results for prediction

Discussion

- Limitations
  - Some collinearity in predictors
    - Ex) pelvic incidence and sacral slope
    - Could reduce precision of estimation/classification, and in turn, statistical power
  - Grade of spondylolisthesis had a high mean decrease in Gini importance
    - Could dominate classification algorithm and bias estimation.
- Recommendations for the future:
  - Develop more condition specific classification algorithms (as opposed to a one-for-all-spinal-conditions classification), and be more cautious on predictions selection.
- Conclusion: The results of this study indicate that both the SVM and RF models have achieved a relatively satisfying level of precision in classifying spinal conditions.

Thank you for your attention!

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