Machine Learning Can Predict Level of Improvement in Shoulder Arthroplasty

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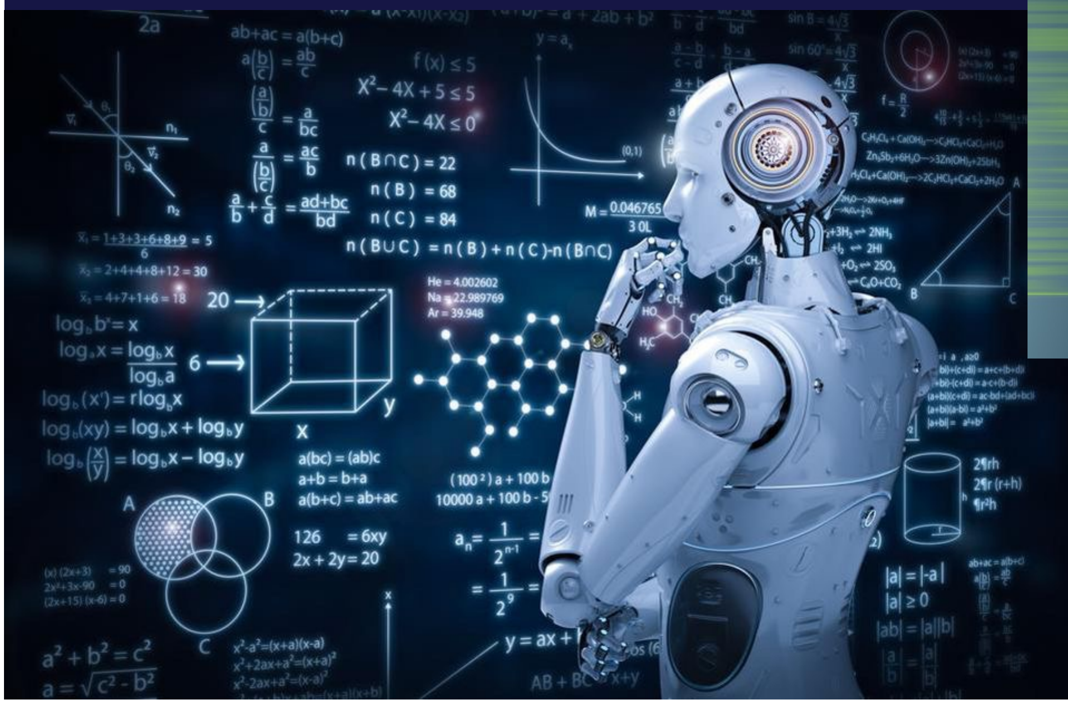
PGY-5

Machine Learning



Everyday Life

Rationale

- Achieving good outcomes is a prime goal of surgery
- Reliable outcome prediction benefits patient and surgeon
- Machine learning has shown initial promise in outcome prediction

Study Question

Can pre-operative data be combined and analyzed via machine learning algorithms to predict level of improvement at minimum 2 year follow up after shoulder arthroplasty?

JB&JS

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- Retrospective
- 472 patients, 1° glenohumeral OA
  - 431 TSA, 41 RSA; 56% male; mean age 68
- Minimum 2 year follow up

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Methodology

- Input data for machine learning algorithms
  - Patient demographics
  - CT-based morphology (bone and soft tissue)
  - Pre-op & post-op ASES scores

- Level of improvement assessed by change in ASES score from pre-op to 2 year post-op

Levels of ASES Improvement

A

- Improvement < 29

B

- Improvement of 29 - 55

C

- Improvement > 55

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3 Machine Learning Models Created

- Model 1
  - Included all the aforementioned data variables
- Model 2
  - Omitted morphology data
  - Only included demographic & ASES data
- Model 3
  - Omitted ASES data
  - Only included demographic & morphology data

Results

Level of ASES Improvement

Approx. 41 point improvement at 2 years post-op

A = 137 B = 172 C = 163

	Mean Score		
Measure	All Patients (N = 472)	TSA (N = 431)	RSA (N = 41)
Preop. ASES	36.5	37.0	31.1
2-yr ASES	78.1	78.5	73.5
Difference in ASES	41.6	41.5	42.4

Predictive Ability

- Excellent overall predictive ability
- Most accurate when all input data incorporated
  - Model 1

TABLE V Tier as Predicted by Different Models Using Change in ASES Score Beyond 2-Year-Range Follow-up

	Class*		
	A	B	C
Model 1 predicted tier			
Probability			
p(A)	$\boxed{0.94}$	0.04	0.04
p(B)	0.05	$\boxed{0.95}$	0.03
p(C)	0.02	0.01	$\boxed{0.94}$
Sensitivity	0.91	0.94	0.98
Model 2 predicted tier			
Probability			
p(A)	0.93	0.16	0.14
p(B)	0.06	0.80	0.13
p(C)	0.01	0.03	0.73
Sensitivity	0.57	0.81	0.96
Model 3 predicted tier			
Probability			
p(A)	0.77	0.17	0.06
p(B)	0.18	0.72	0.10
p(C)	0.13	0.16	0.71
Sensitivity	0.6	0.72	0.86

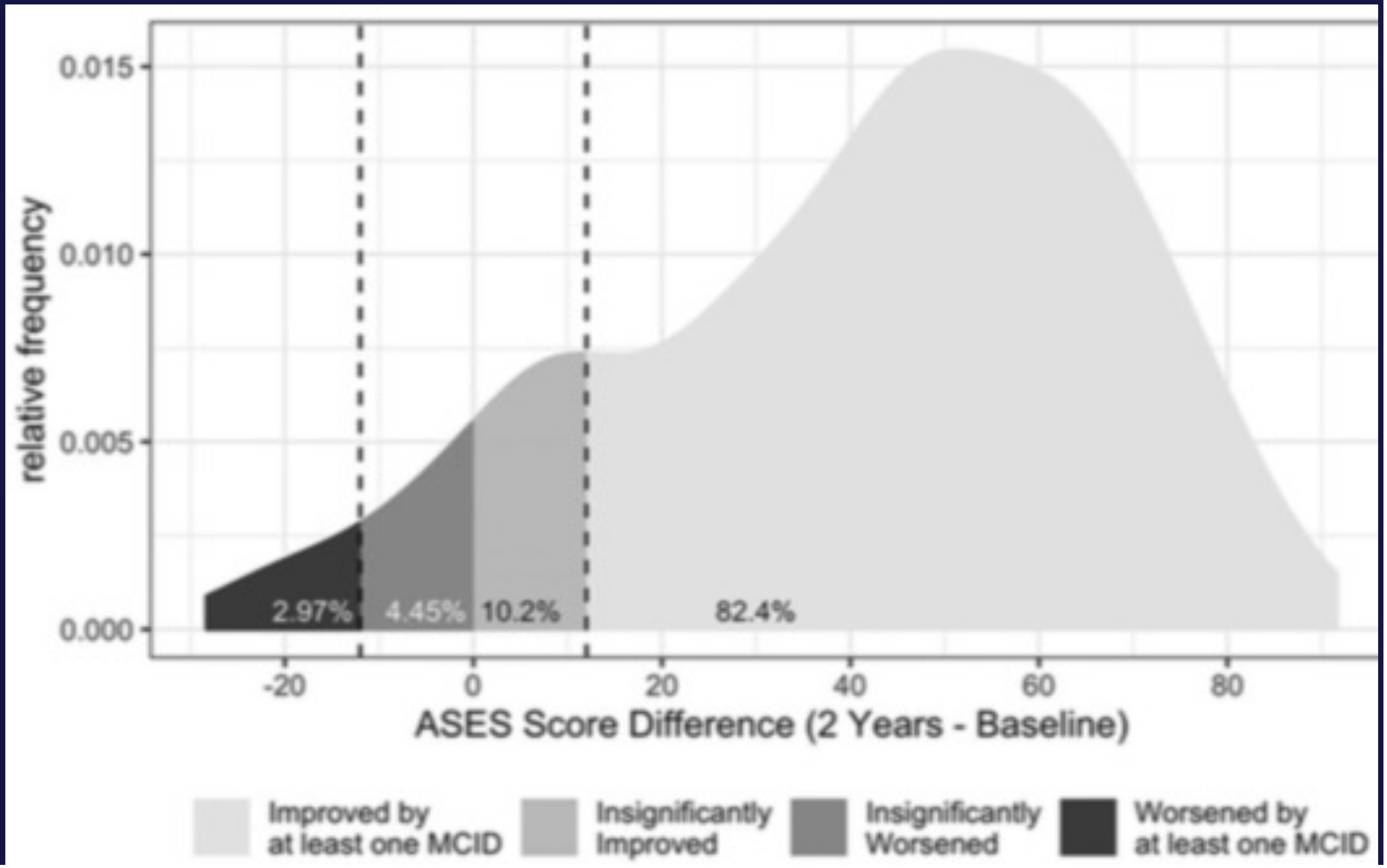
Outcome Distribution

92.6% of patients exhibited improvement

82% significant

MCID = 12

Minimum clinically important difference



Conclusion

Using pre-operative data, Machine Learning models can accurately predict level of improvement after shoulder arthroplasty

Limitations

- Highly specialized and complex analysis
  - Not readily available
- Retrospective
  - Potential for missing follow up data or sampling error
- Generalizability & “Over-fitting”
  - Future direction?

Strengths

- High level of predictive accuracy
- Data set with granular input of variables
- Able to parse relative importance of input variables
  - Future studies?
- Consecutive patients, reproducible surgery, single surgeon
  - Stratification of Walch, Goutallier, Tanget sign, and mean ASES improvement are consistent with reported literature

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Questions?

Thank You

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