# Machine learning improves image analysis prognosis and diagnosis in cardiac imaging

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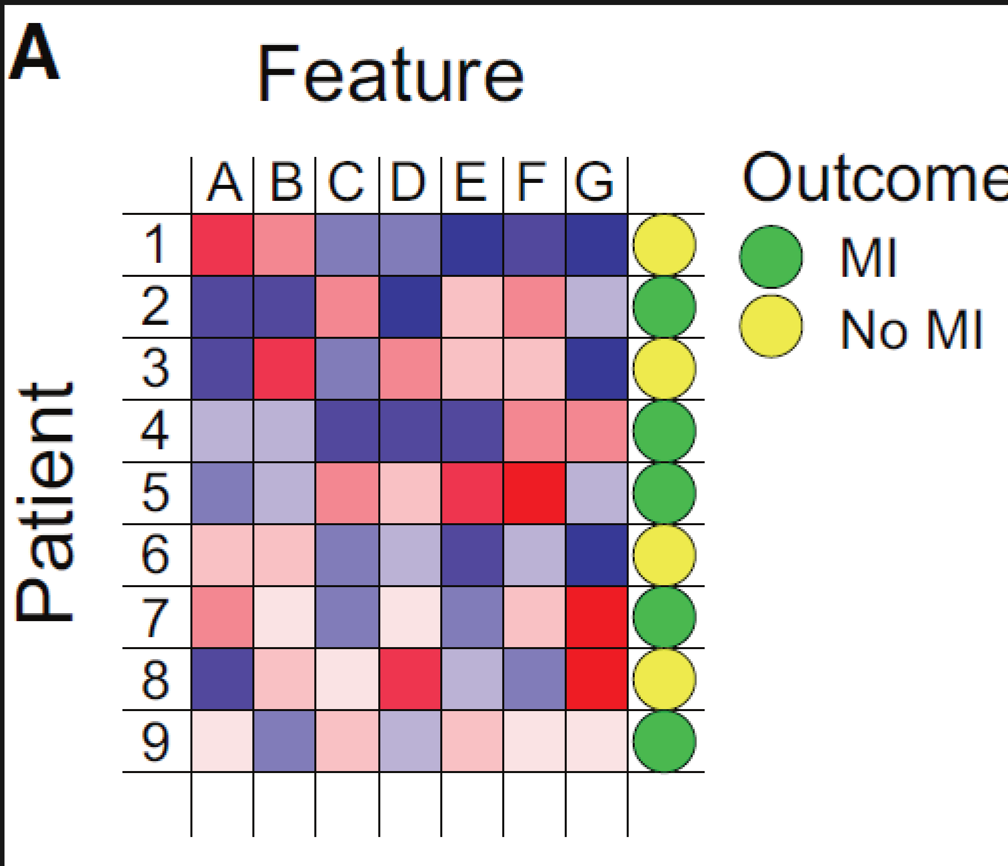
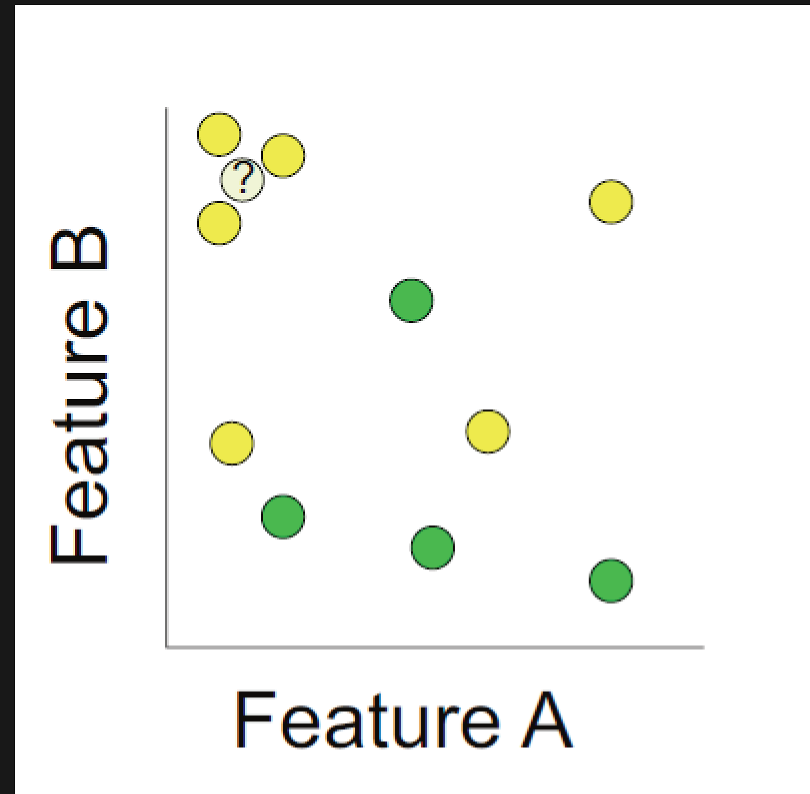
# Machine learning

Prediciting anything that can be predicted
No particular model is assumed unlike in statistics
Testing data <u>always</u> separate from training data

# Simple machine learning



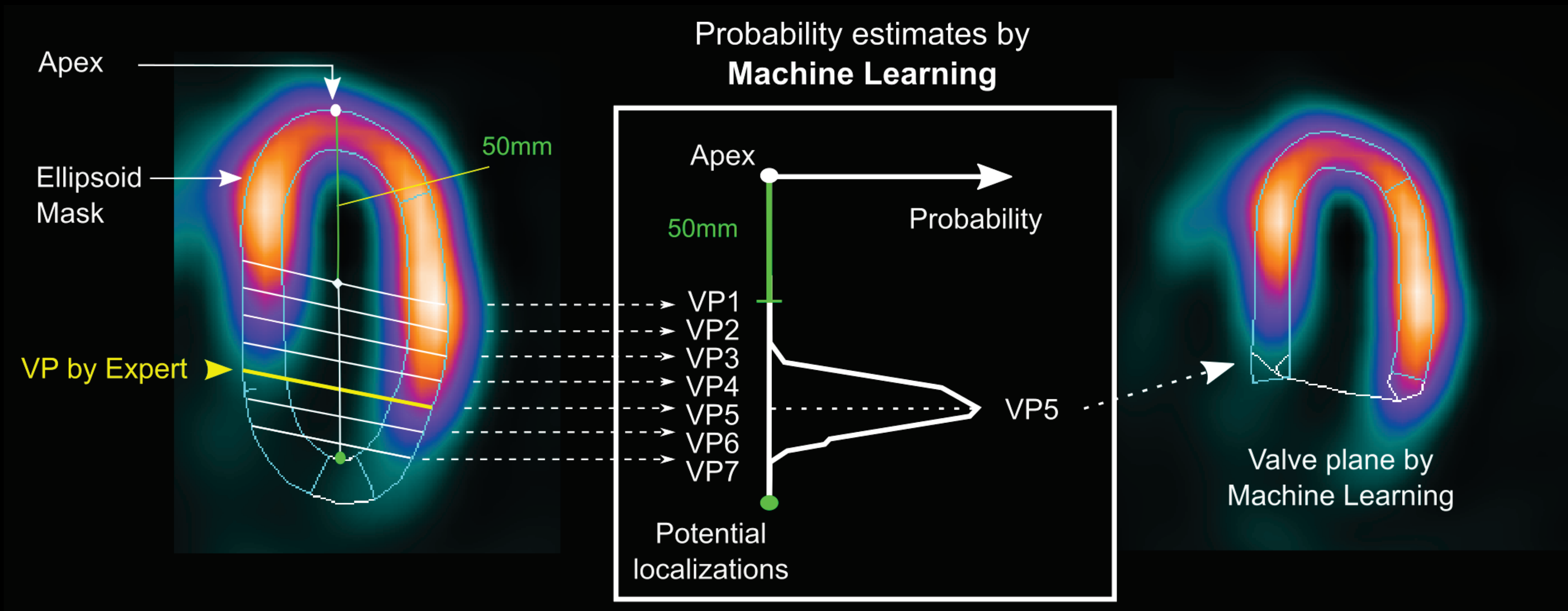



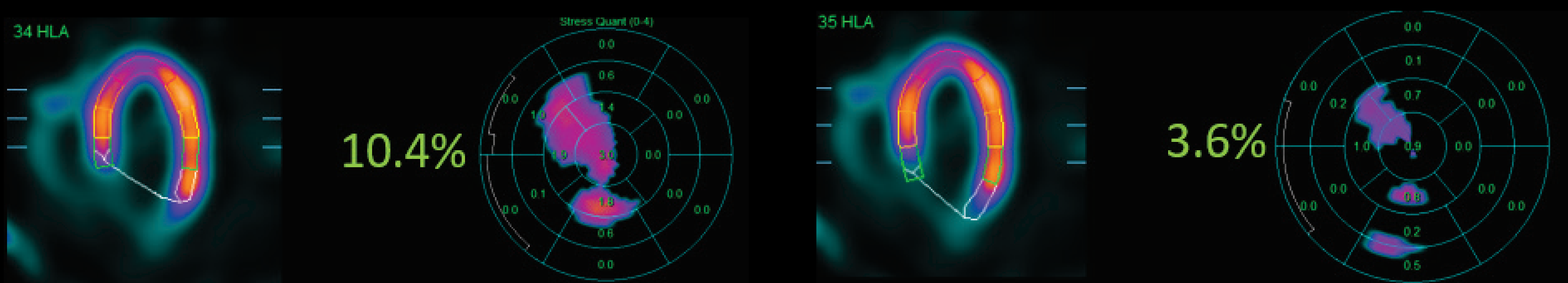

The k-nearest neighbor algorithm assigns outcome based on the most similar training examples

MI -myocardial infarction

*Deo RC Circulation 2015*

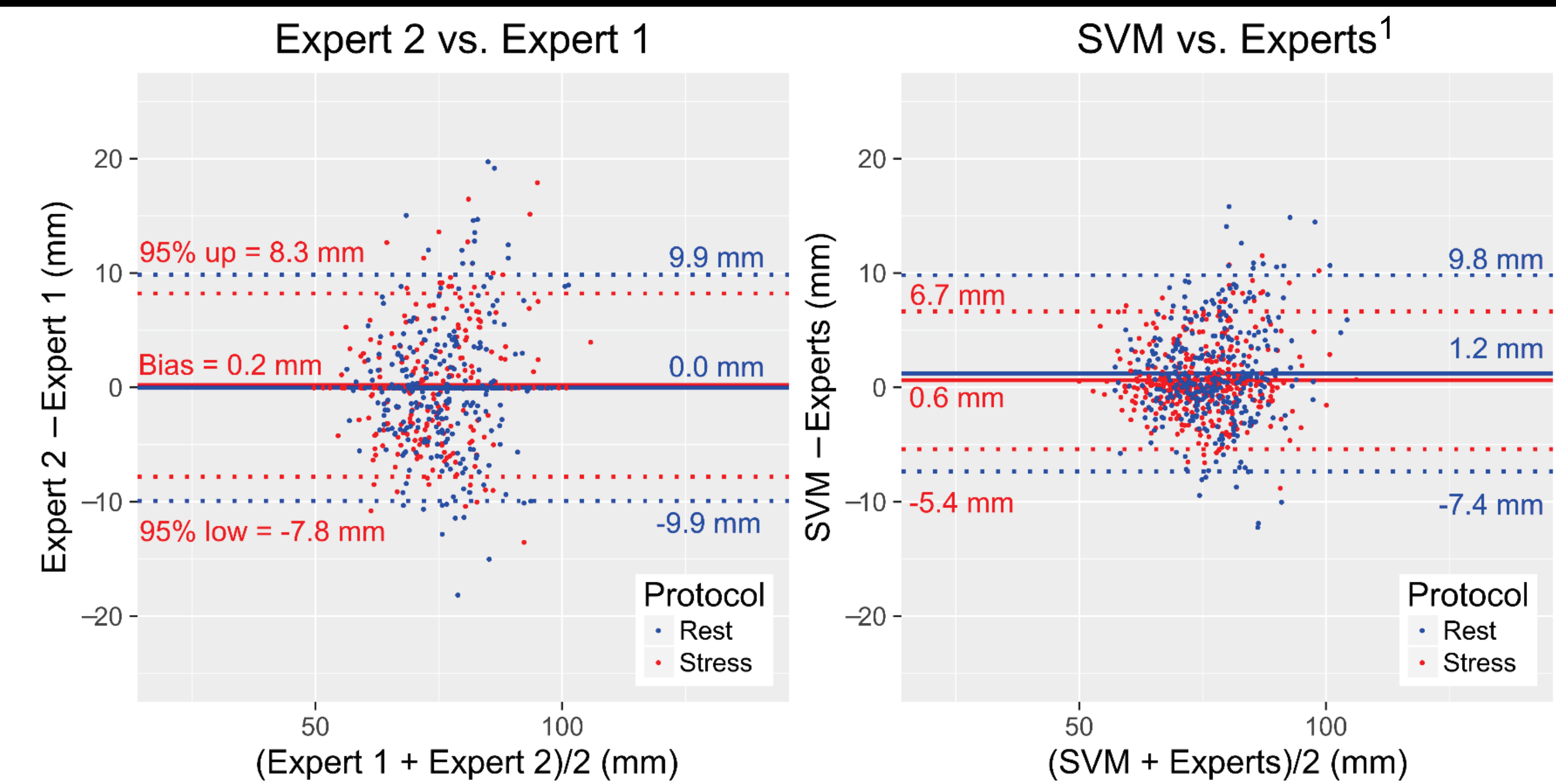
# Machine Learning: valve plane localization



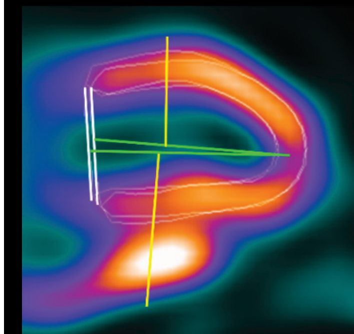




Betancur et al JNM 2016 (in press)

# Machine learning agreement with Experts

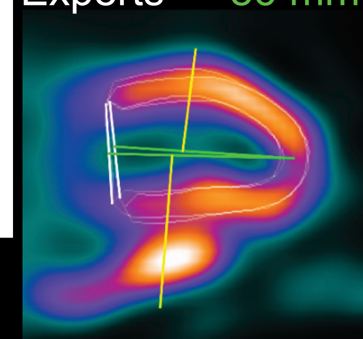



Expert 1 = 85 mm



Expert 2 = 87 mm

Experts[1] = 86 mm



SVM = 88 mm

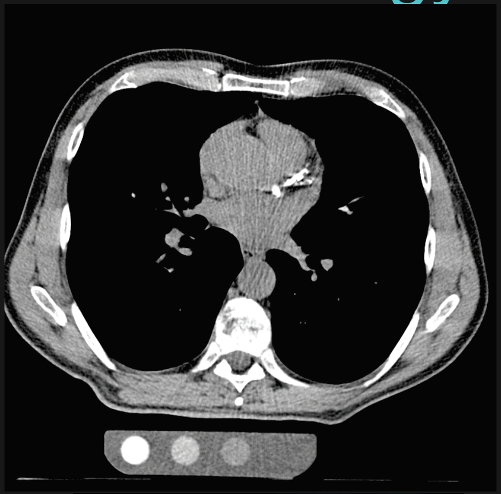
Valve plane agreement (95% CI) between support vector machines (**SVM**) and experts was lower than inter-expert agreement ($p<0.01$)

[1] Experts = (Expert 1 + Expert 2)/2

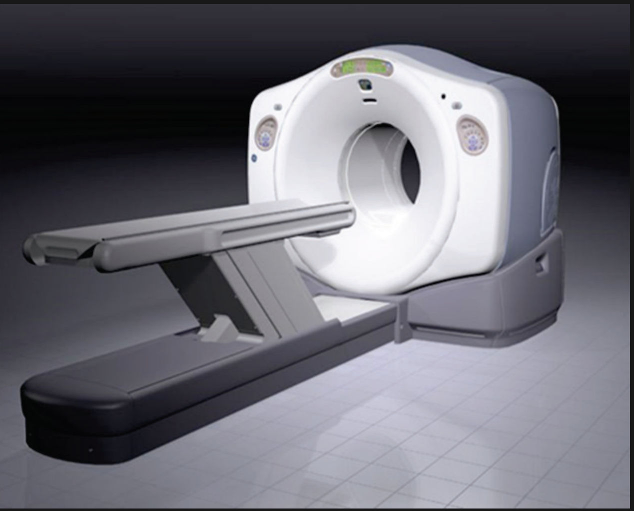
Betancur et al JNM 2016 (in press)

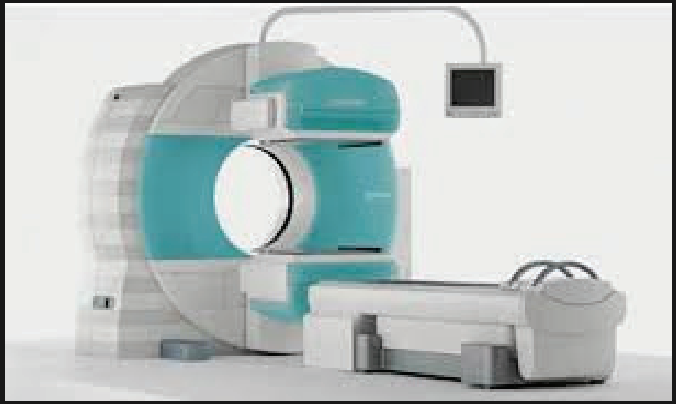
# Higher level machine learning

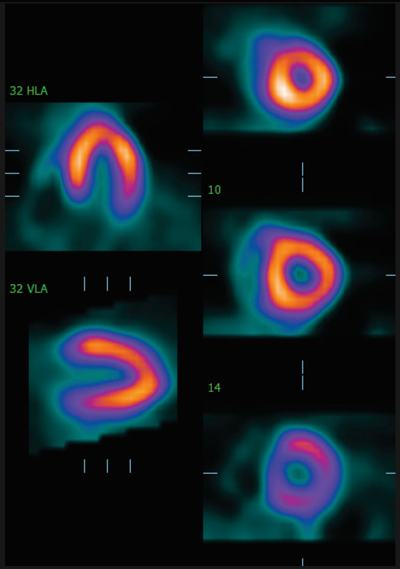
## Coronary calcium scan + nuclear cardiology



- Coronary calcium score predicts cardiovascular events
- But how to interpret combined calcium and nuclear findings ?





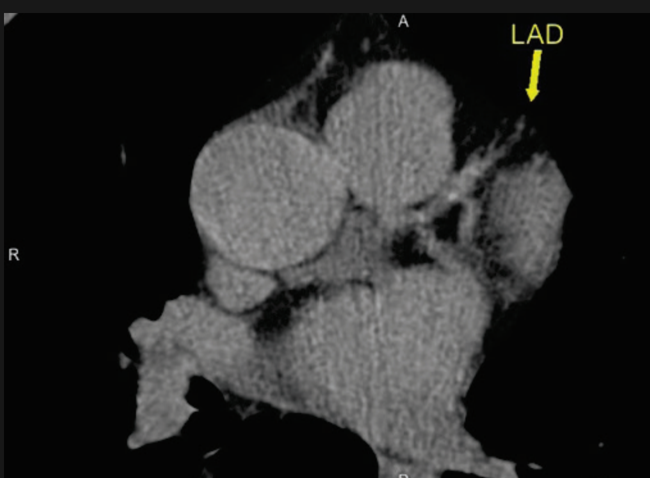



Hybrid PET/CT SPECT/CT can obtain MPI +calcium scan

# Simple machine learning by logistic regression

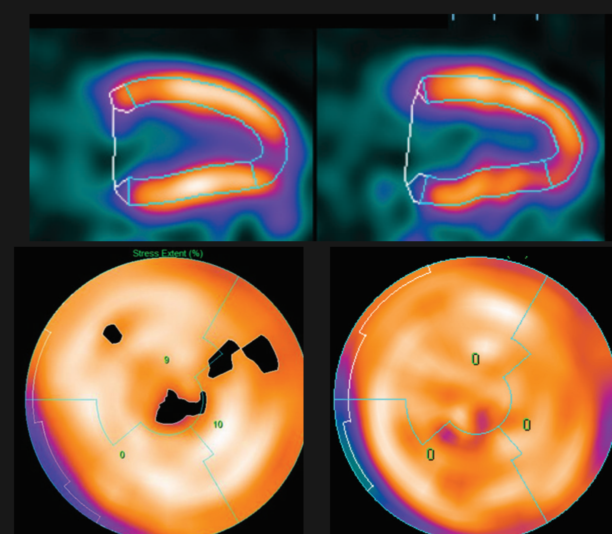
- multivariable logistic regression
- probability score of obstructive disease

$$1/(1 + \mathrm{Exp}(3.65 - 0.34 \times \text{per-vessel ITPD} - 0.39 \times \log(\text{per-vessel CAC} + 1)))$$




+

Stress Rest



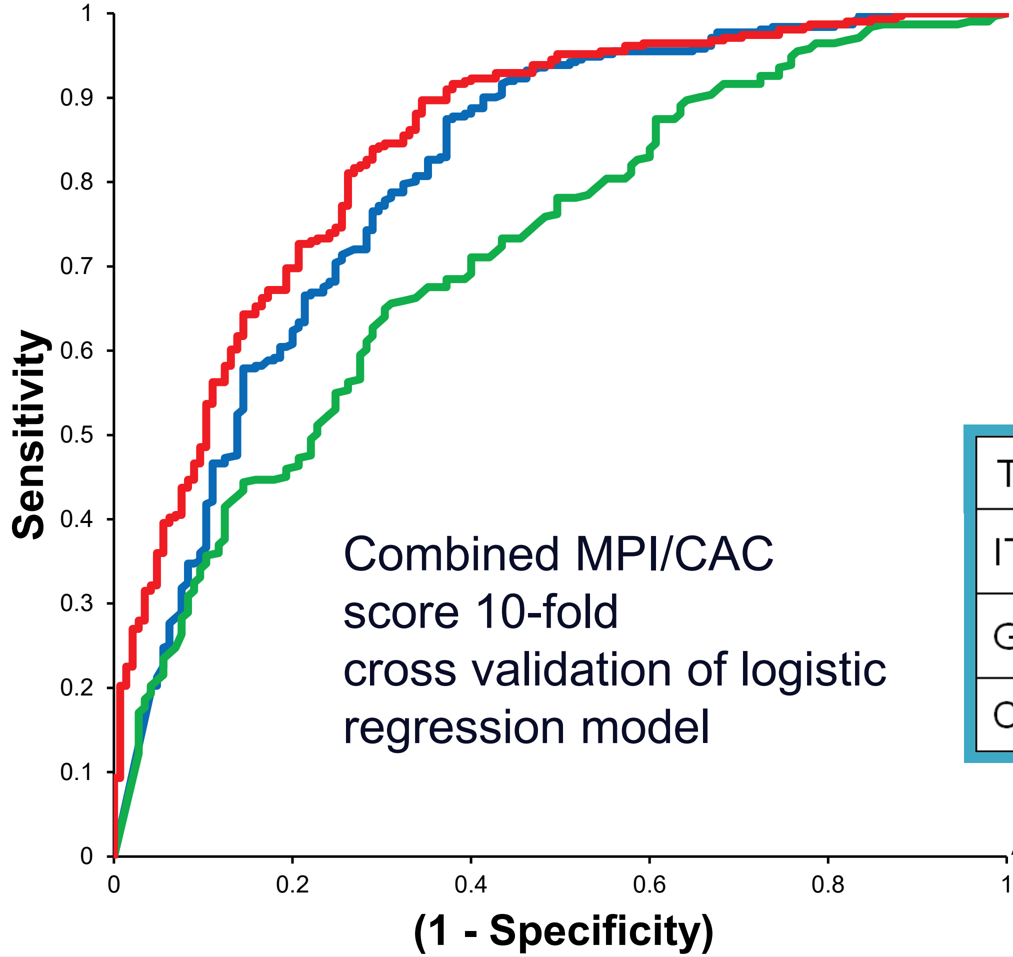
Obstructive disease score

Brodov et al JNM 2015

# Hybrid perfusion/calcium score

Feature 1: ITPD –ischemic perfusion
Feature 2: CAC –coronary artery calcium

Quantitative combined hybrid PET/CAC score (N=456) vessels




| Test | AUC | 95% CI |
|---|---|---|
| ITPD | 0.81 | 0.75-0.85 |
| Global CAC | 0.72 | 0.66-0.76 |
| Combined* | 0.84 | 0.80-0.88 |

AUC=Area under curve
*$p < 0.05$ vs. PET alone

Brodov et al JNM 2015

# Adding more features Can we predict revascularization after MPI by machine learning ?

First step:

Selecting relevant knowledge (features) for the machine learning

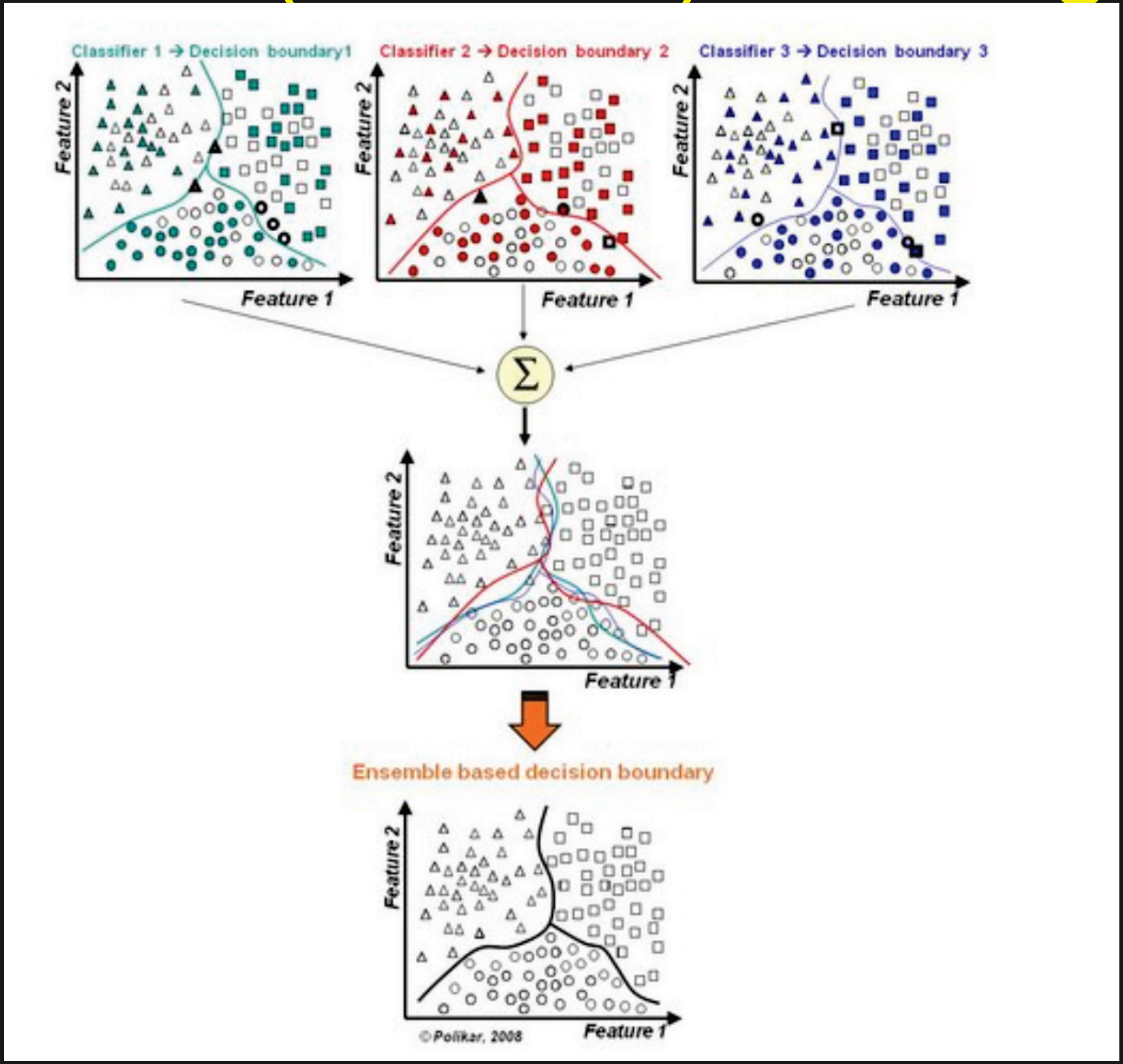
**Table 2.** Ranking of the features by the automated feature selection algorithm

| Features | Ranking |
|---|---|
| Combined supine/prone TPD* | 0.1876 |
| Supine stress TPD* | 0.18 |
| ST-depression at rest* | 0.0394 |
| ECG response during exercise* | 0.0341 |
| Supine rest TPD* | 0.0336 |
| Post-ECG likelihood of CAD* | 0.032 |
| Clinical response during exercise* | 0.0305 |
| Transient ischemic dilation (TID)* | 0.0265 |
| Gender* | 0.232 |
| Stress ejection fraction* | 0.0188 |
| End-systolic volume (ESV) | 0.018 |
| Resting BP* | 0.0158 |
| History of diabetes mellitus* | 0.0136 |
| Age | 0 |
| Heart rate/peak heart rate/peak BP (3) | 0 |
| History of hypertension | 0 |
| Pretest likelihood of CAD (before ECG) | 0 |
| Clinical response | 0 |
| Family history of CAD | 0 |
| History of hyperlipidemia | 0 |
| Smoking | 0 |
| Height/weight/body mass index (3) | 0 |
| Exercise duration | 0 |
| METs achieved | 0 |
| Claudication | 0 |
| Symptoms at rest | 0 |
| Rest ejection fraction | 0 |
| End-diastolic volume | 0 |

*CAD*, Coronary artery disease; *METs*, metabolic equivalent of task; *BP*, blood pressure (number of features given in brackets if multiple).
*Selected features.

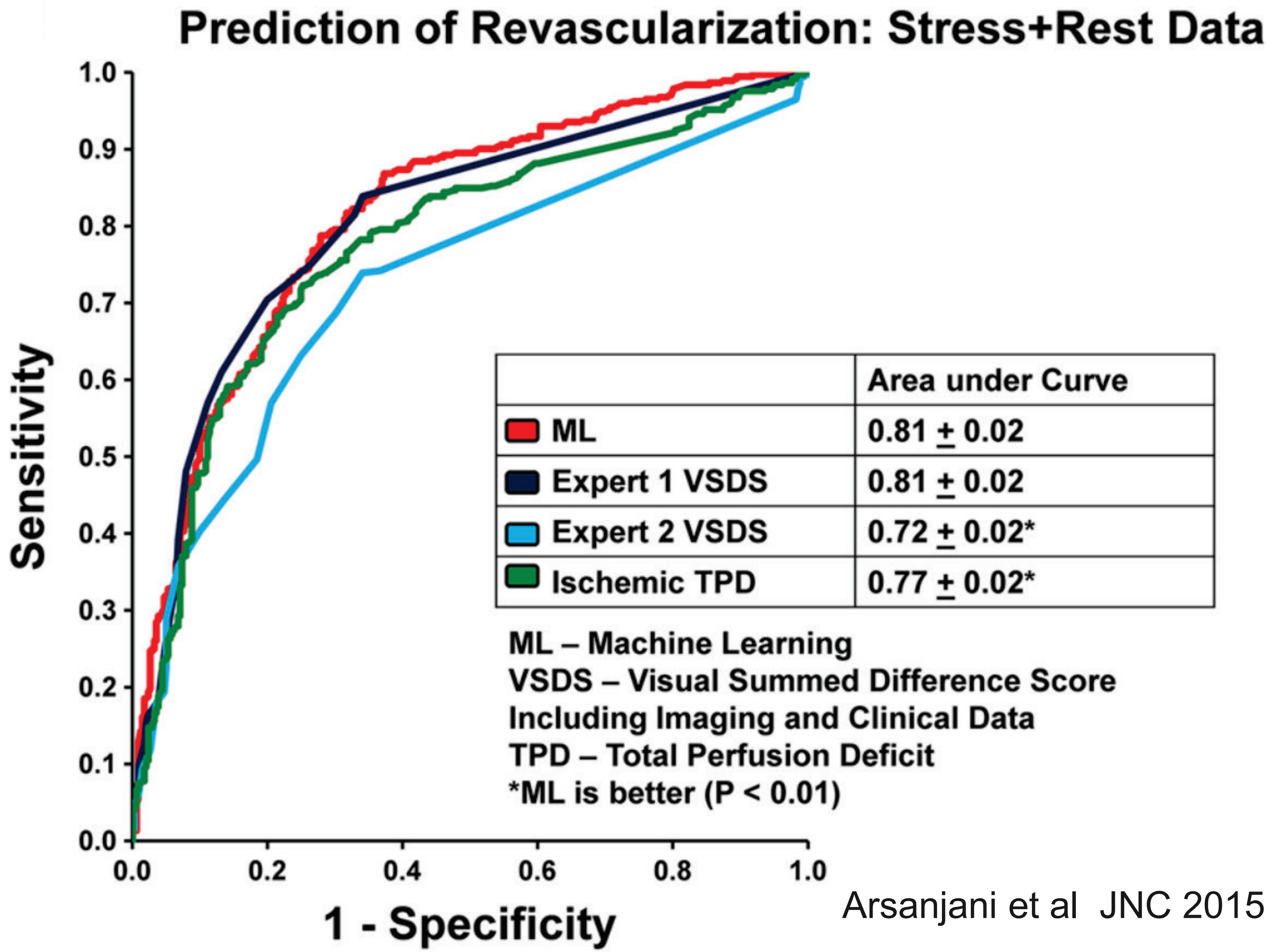
*Arsanjani et al JNC 2014*

# Ensemble (boosted) learning



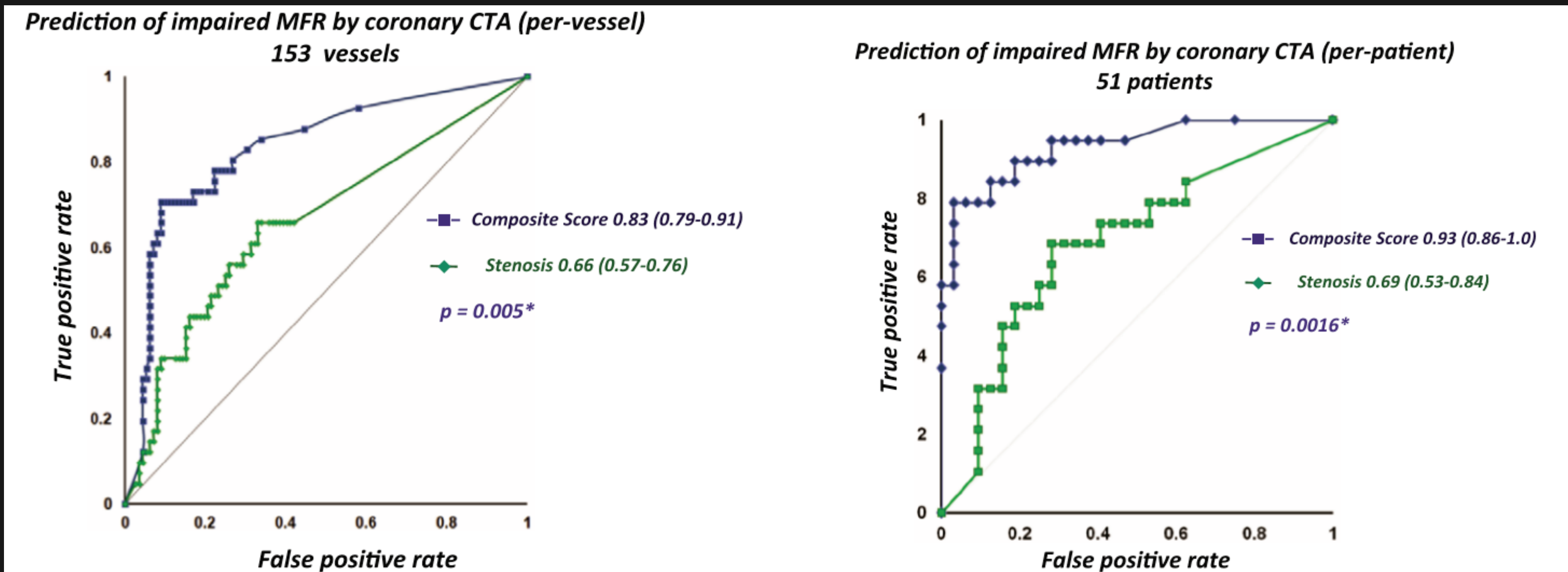

http://magizbox.com

# Can we predict revascularization after MPS by machine learning ?

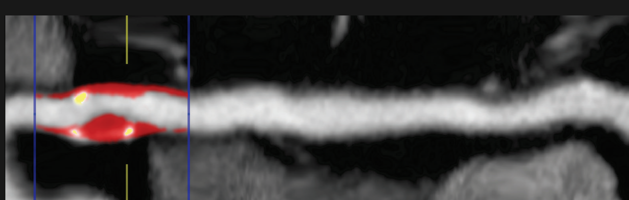


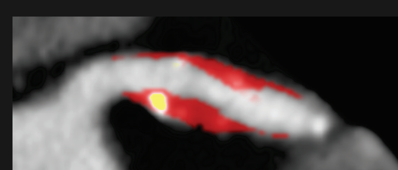

Arsanjani et al JNC 2015

# CTA quantification predicts myocardial flow reserve by $^{13}NH3$ PET

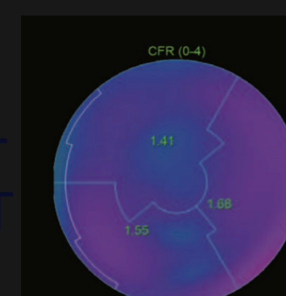



CTA automatic plaque characteristics( 5 features), myo mass, age/gender
LogitBoost ensemble learning 10-fold cross validation per-vessel per-patient



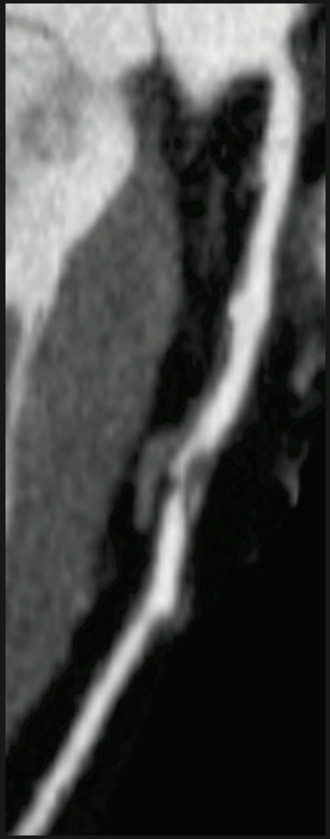


Machine learning




Dey et al Circ Cardiovasc Imaging 2015

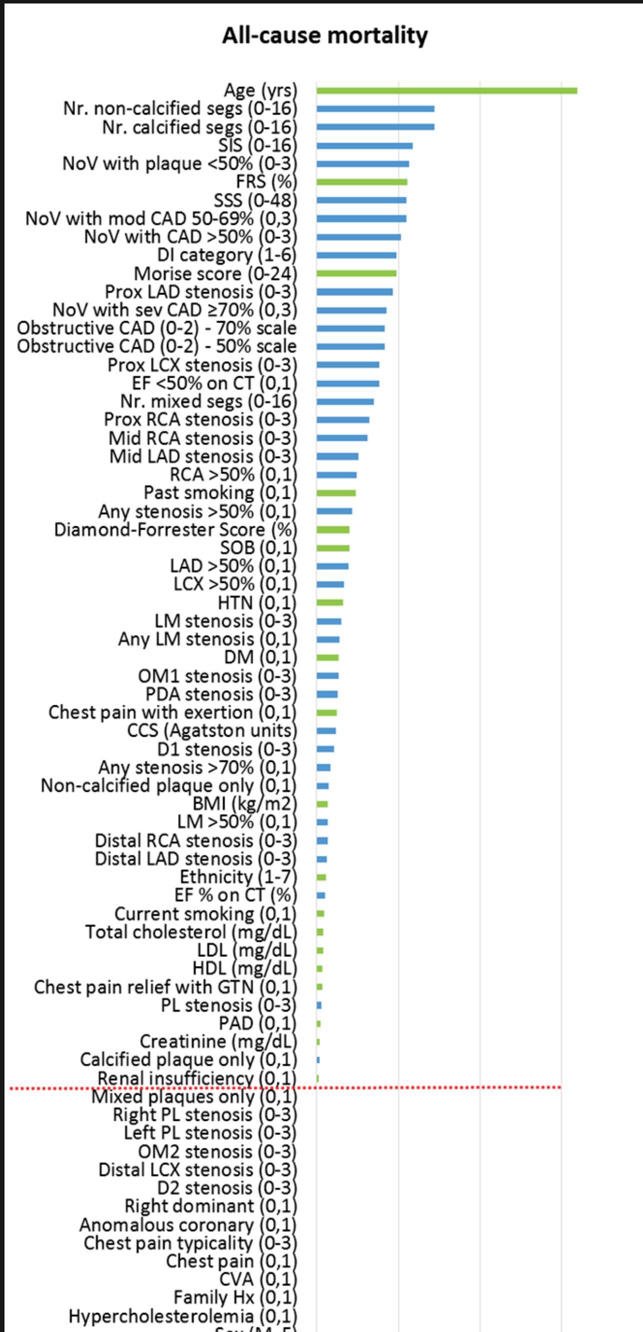
# Outcome prediction by machine learning: Interpreting CT image features and clinical data in CONFIRM registry

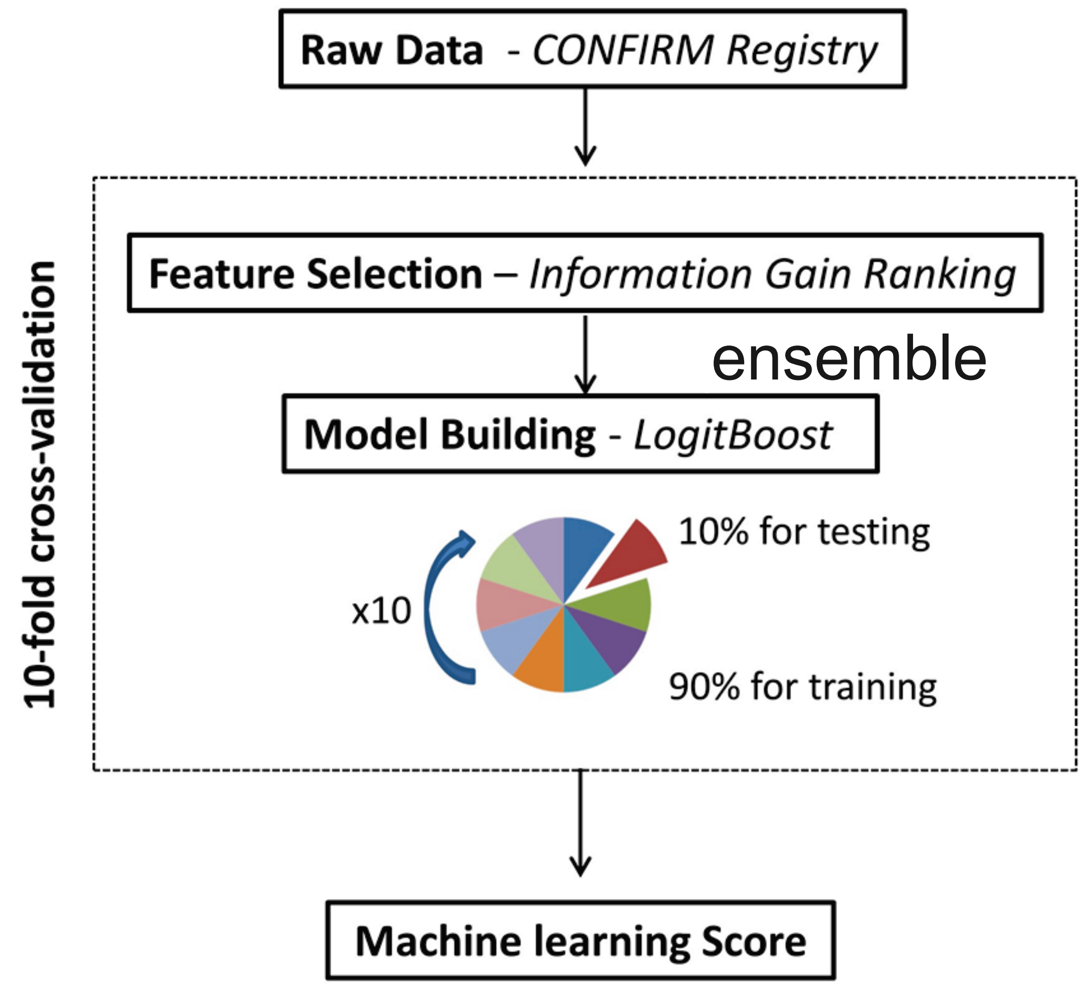


CONFIRM - registry of over 16, 000 cases
From 12 centers with CT angiography findings
and mortality follow up Confirm PI: Dr. Min

*Motwani M et al EHJ 2016*

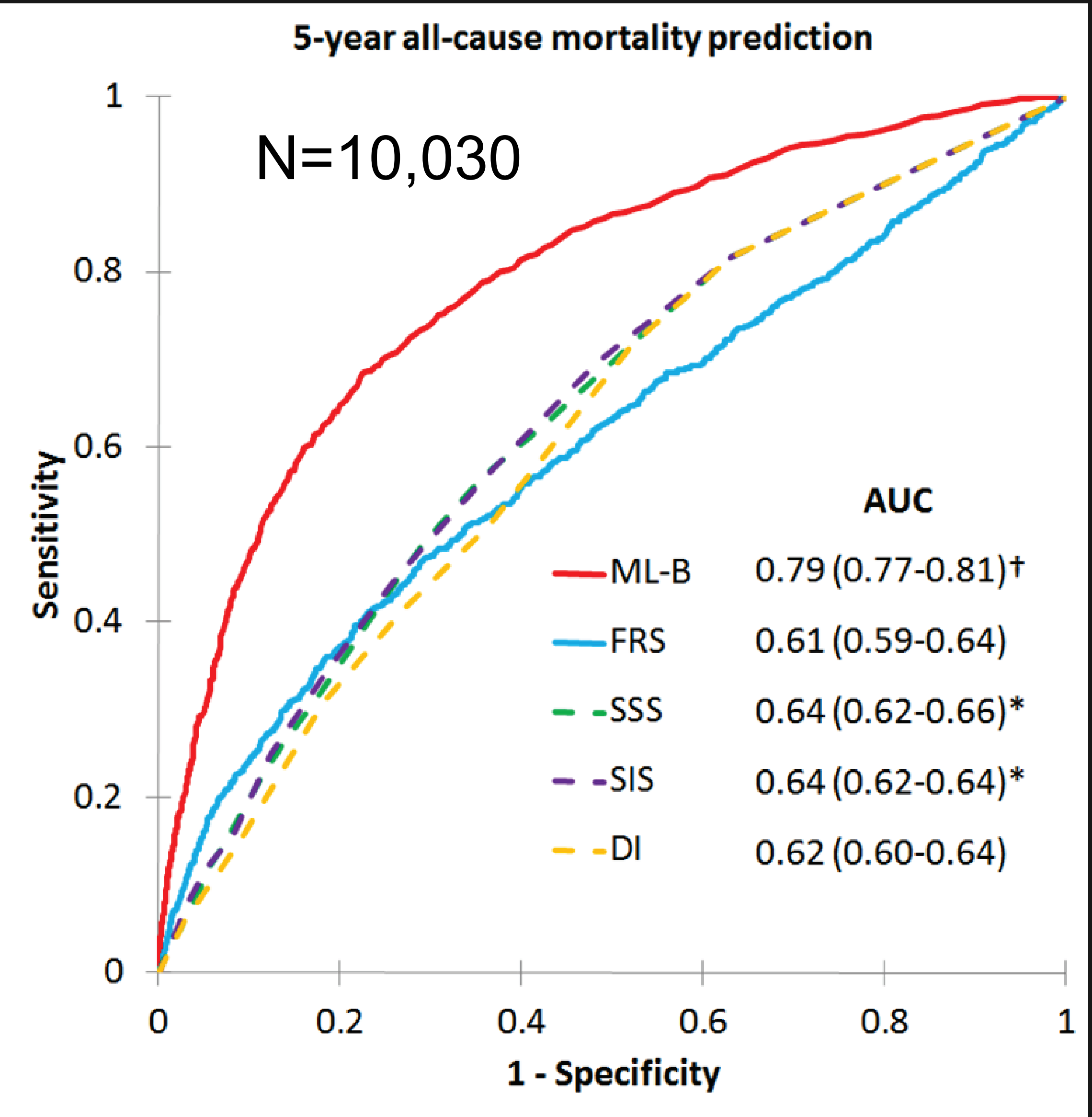
# Feature selection and learning




*Motwani M et al EHJ 2016*

# Death prediction by ensemble machine learning over standard risk scores




ML-B -boosted machine learning

FRS –Framingham risk score

SSS –segmental stenosis score

SIS –segmental involvement score

DI -Duke index

AUC –area under curve

*Motwani M et al, EHJ 2016*

# Risk re-classification by machine learning

| FRS risk category | ML-boosting risk category | | | |
|---|---|---|---|---|
| | Low | Intermediate | High | Total |
| ***Death, n*** | | | | |
| Low | 38 | 89 | 108 | 235 |
| Intermediate, | 22 | 124 | 60 | 206 |
| High | 11 | 108 | 185 | 304 |
| **Total** | **71** | **321** | **353** | **745** |
| ***No Death, n*** | | | | |
| Low | 2193 | 1578 | 256 | 4027 |
| Intermediate | 1209 | 1700 | 209 | 3118 |
| High | 487 | 1169 | 484 | 2140 |
| **Total** | **3889** | **4447** | **949** | **9285** |
| **Overall NRI index (95% CI)** | | 0.24 (0.19-0.30) | | p<0.0001 |

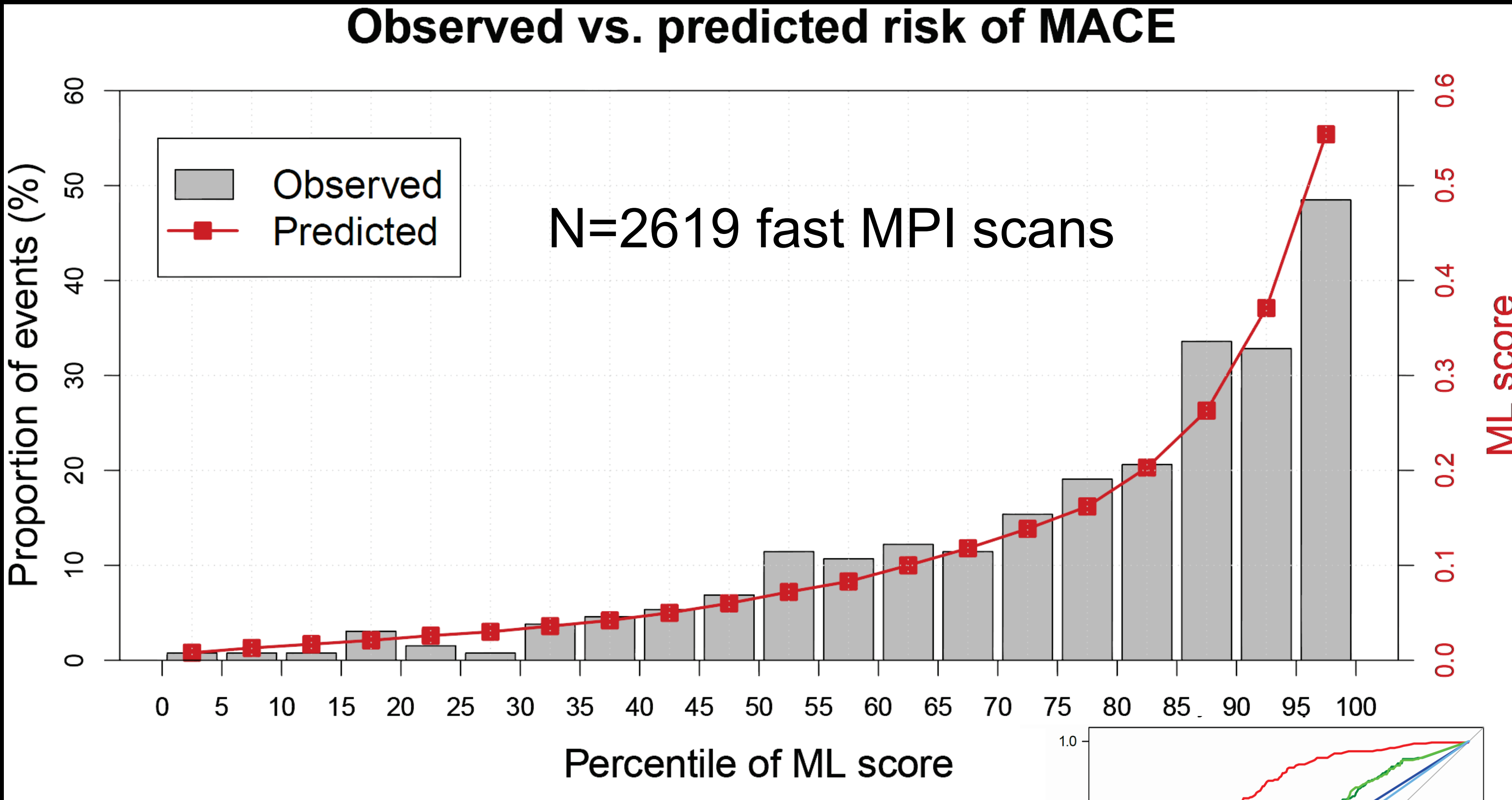
ML: machine learning

FRS: Framingham risk score

NRI –net reclassification improvement

*Motwani M et al EHJ 2016*

# Prediction of 3-year MACE by MPI and machine learning



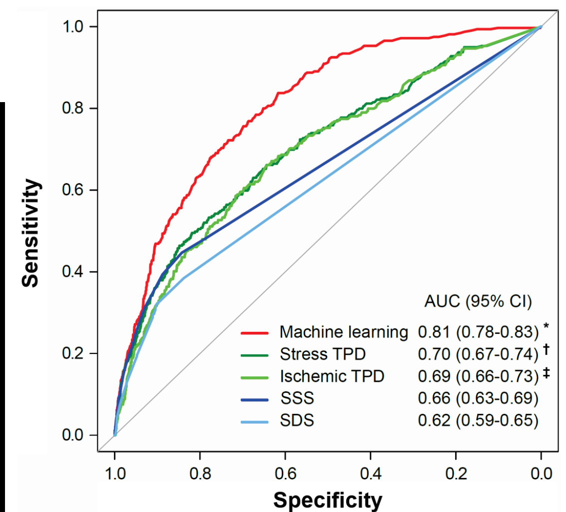

*Machine learning for automated prediction of major adverse coronary events after myocardial perfusion imaging  Otaki Y, ASNC 2016*

ML machine learning

MACE –major adverse cardiovascular events

TPD –total perfusion deficit

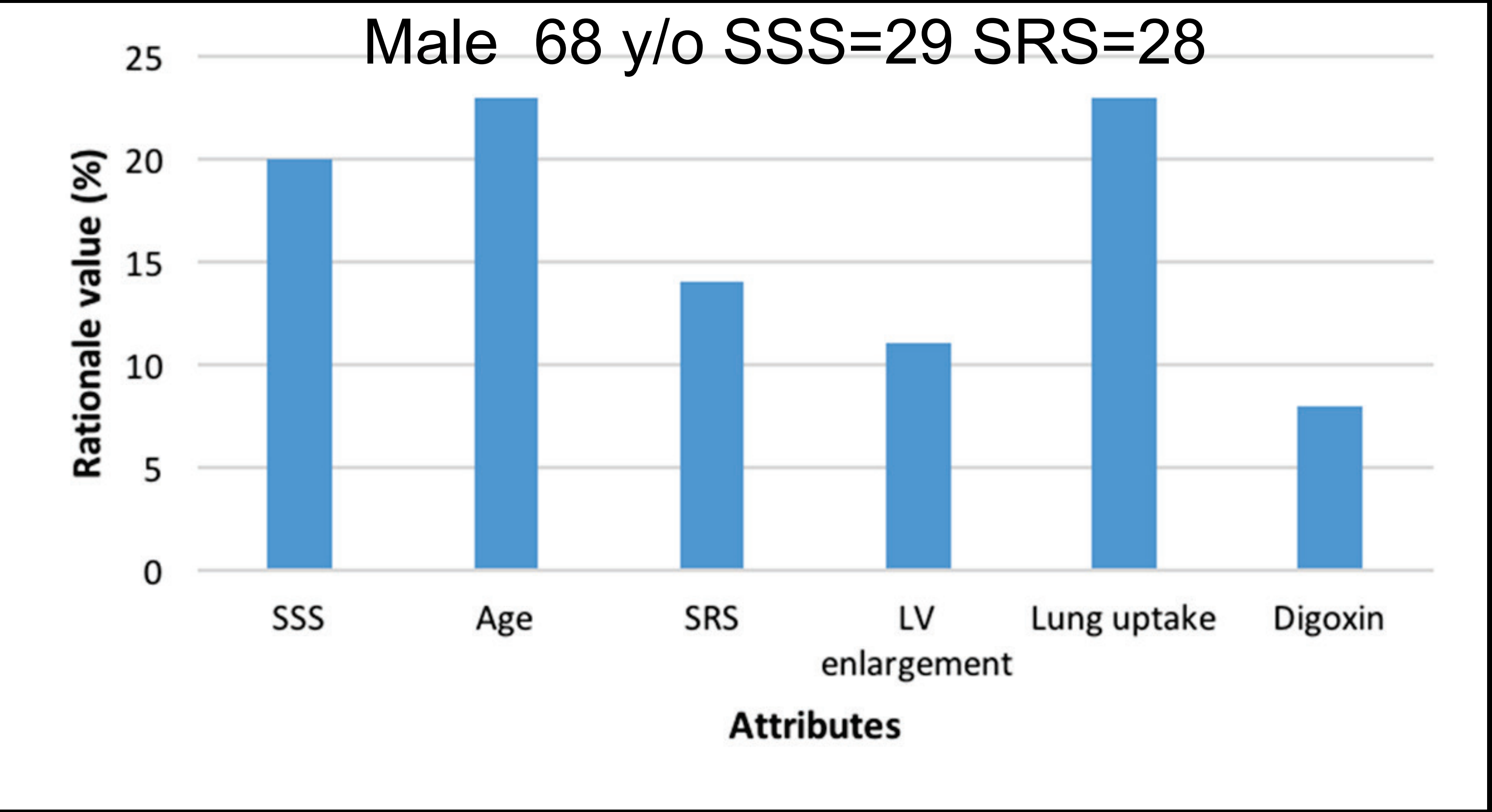
SSS/SDS –visual summed stress/difference score



# Does it have to be a “black box” ?

## ML prediction rationale for a given patient

Alonso H et al, A Simple Model for Prediction of Cardiac Death ASNC 2016




**In a clinical setting, it will be possible to interpret an individual ML assessment**

# Machine learning registry

## Aiming to include > 2,000 cases with angio 14,000 with follow up

| Site | System | Protocols |
| --- | --- | --- |
| **Cedars-Sinai** | D-SPECT | Sestamibi rest/stress<br>supine/upright |
| **Mount Sinai** | GE 530c | Low-dose sestamibi<br>supine/prone (some stress-only) |
| **Mayo Clinic** | D-SPECT | Sestamibi rest/stress supine/upright |
| **Aspire, Kansas City** | DSPECT<br>Siemens Symbia SPECT/CT | Low-dose sestamibi stress or stress/rest supine/upright<br>~50% stress-only AC for Symbia |
| **Columbia Medical center, New York** | GE 530c | Sestamibi prone/supine |
| **Assuta Medical Center Israel** | GE 530c | Low dose sestamibi<br>supine/prone |
| **Oregon Heart and Vascular Institute** | D-SPECT | Sestamibi rest supine<br>stress supine/upright |
| **Zurich University Hospital** | GE 570c SPECT/CT<br>GE Ventri/VCT SPECT/CT | Low-dose tetrofosmin stress/rest<br>AC for all |
| **Ottawa Heart Institute** | GE 530c<br>GE Infinia SPECT/CT | Low-dose tetrofosmin<br>AC for GE Infinia |
| **Yale** | GE570c SPECT/CT<br>GE Infinia SPECT/CT | Stress/rest sestamibi protocols.<br>AC for all |
| **Brigham and Women's Hospital** | D-SPECT<br>Siemens Symbia SPECT/CT (IQ·SPECT) | Same-day, dose-dependent rest/stress sestamibi.<br>Supine/upright for D-SPECT<br>AC for Symbia |

NIH R01 HL089765

# Machine learning in nuclear cardiology

- Machine learning (ML) combines multiple imaging and clinical datapoints in one score.
- ML can be used to train image segmentation
- ML can predict disease, intervention, or outcomes in terms of post-test probability
- Quantitative computer interpretation will help clinicians <u>find the right answer </u>for a given patient