

CT Machine Learning Analysis of Calcifications to Predict Abdominal Aortic Aneurysm Rupture

Mohamed Mansouri (Université de Montréal), Dr. Gilles Soulez (CHUM), Dr. Éric Thérasse (CHUM), Dr. Carl Chartrand-Lefebvre (CHUM)

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Conflict of Interest

We have no relation to declare with a non-profit or for-profit organization.

I. Background

- In the US, AAA prevalence around 1.4% in those aged between 50 and 84 (1.1 million) (1). Although it is most often an asymptomatic condition, the lethality of ruptured AAAs still ranges between 80 and 95% (2).
- Main predictor of rupture risk is AAA DMax(3). Present-day model based on maximum diameter and sex only yields a 60% sensitivity (95% CI, 47%-72%) for rupture risk prediction (4). We need new parameters.
- Literature is conflictual regarding the role of aortic calcification in AAA rupture (5-13). Only a few clinical studies examined the link between aortic calcifications and AAA rupture (9, 11, 12). The goal of this project was to assess whether aortic calcification can improve AAA rupture prediction.

II. Methods

- 80 patients treated for a ruptured AAA between January 2001 and August 2018 at the CHUM or MUHC
- Matched with 80 non-ruptured patients treated electively for a non-ruptured AAA between January 2001 and August 2018 at the CHUM or MUHC based on maximal AAA diameter (+/- 10%), age (+/- 12 years), sex and contrast status of the preoperative scan
- Crossed medical archives AAA repair treatment codes with RIS-PACS and ODIN imaging databases mention of ruptured/non-ruptured AAA to end-up with a list of ruptured/non-ruptured AAAs with imaging

II. Methods

- Rupture definition: mention of rupture in the preop CT radiology report.
- Calcification segmentation performed on ITK- Snap with a 500 HU lower threshold to make sure IV contrast on C+ scans is properly removed, AAA wall segmentation on ORS
- Machine learning analysis: 1st run of all initial data with ExtraTrees Classifier from which 5 most important variables were retained and computed through XGBoost machine learning algorithm.
- Compared final machine learning AUC with AUC of AAA rupture prediction based solely on sex and diameter (Tang et al.) (4):
 - similar patient population (CHUM and MUHC)
 - we chose to match our patients to have a high quality univariable analysis
 - given patients were matched, it was not possible to compute an AAA rupture prediction model using machine learning based on sex and diameter

Figure 1- Study flowchart for patients with ruptured AAAs. Patients with ruptured AAAs were matched to patients with non-ruptured AAAs using trial and error.

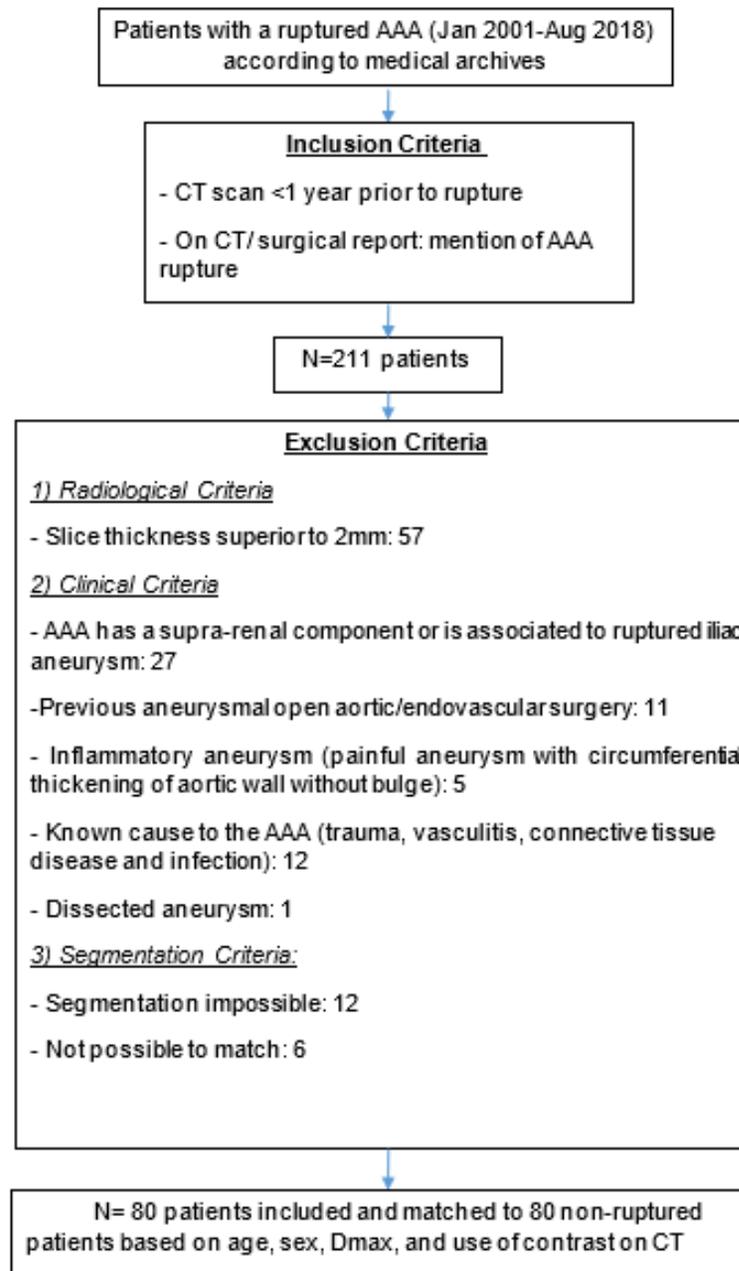
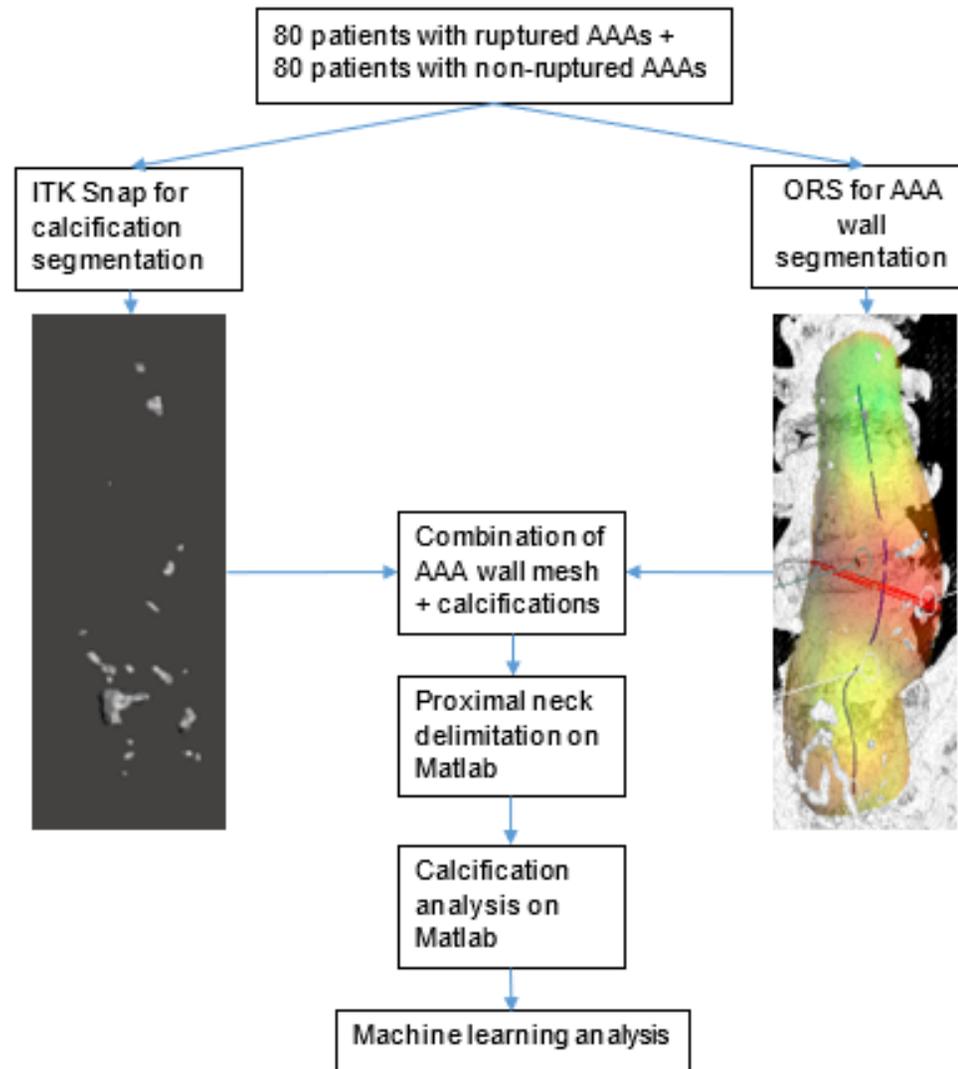


Figure 2 - Project workflow Left picture represents a segmented wall calcification of an infrarenal AAA on ORS (AAA wall segmentation software). Right picture represented a segmented AAA infrarenal wall. The black line represents the centerline and the red ellipse, the maximal diameter. Right picture represents segmented aortic wall calcifications on ITK Snap (AAA calcification segmentation software). Original work.



III. Results

- Mean age of patients was 74.0 ± 8.4 years and 89% were men. AAA diameters were equivalent in both groups (80.9 ± 17.5 vs 79.0 ± 17.3 mm, $p= 0.505$).
- Ruptured aneurysms contained a smaller number of calcification chunks than the non-ruptured (18.0 ± 17.9 vs 25.6 ± 18.9 , $p=0.010$) and were less likely to have a proximal neck than the non-ruptured (45.0% vs 76.3% , $p<0.0001$).
- In the machine learning analysis, 5 variables were associated to AAA rupture: proximal neck, antiplatelets, calcification number, Euler distance between calcifications and standard deviation of the Euler distance between calcifications.
- The model including these 5 variables yielded an area under the curve (AUC) of 0.81 ± 0.02 (83% sensitivity and 71% specificity) which was better than a previous study with a similar population reporting a 0.67 AUC (95% CI, 0.58-0.77%) (60% sensitivity and 77% specificity) for sex and diameter only.

III. Results (Univariate analysis with dmax, age, sex matching)

Table 1. Demographic profile of patients (Mean ± standard deviation or N (%)) An additional column representing N of patients with no missing data has been added.

	Ruptured	Non-ruptured	P value	Number of patients	
				Ruptured	Non-ruptured
Age at index date (years)	73.9(8.3)	74.2(8.6)	0.826	80	80
Sex (% men)	71(89)	71(89)	1.000	80	80
CT scan to index date interval (days)	8.1(27.1)	48.5(69.1)	<0.00001	80	80
Tobacco smokers (%)	37(63)	47(64)	0.843	59	73
COPD (%)	19(32)	18(25)	0.337	59	73
Hypertension (%)	39(66)	55(75)	0.244	59	73
Diabetes Mellitus (%)	14(24)	19(26)	0.762	59	73
Coronary Artery Disease (%)	27(46)	39(53)	0.381	59	73
Dyslipidemia (%)	31(53)	43(59)	0.464	59	73
Chronic renal failure (%)	16(27)	20(27)	0.972	59	73
Beta blockers (%)	24(41)	43(59)	0.037	59	73
Anticoagulants (%)	24(41)	35(48)	0.404	59	73
Antiplatelets (%)	31(53)	58(80)	0.001	59	73
Lipid lowering drugs (%)	31(53)	55(75)	0.006	59	73

III. Results (Univariate analysis with dmax, age, sex matching)

Table 2. AAA calcification statistics (mean \pm standard deviation or N (%)) Euler distance is the average distance between every calcification with each other calcification, it is an index of calcification dispersion throughout the aneurysmal wall.

	Ruptured (n=80)	Non-ruptured (n=80)	P value
Neck Presence (%)	36(45)	61(76)	<0.0001
Max AAA Diameter (mm)	80.8(17.6)	79.0(17.3)	0.505
Centerline Length (mm)	129.1(23.9)	131.5(19.5)	0.490
Calcification Volume (mm ³)	635(913)	689(893)	0.707
Calcification Surface (mm ²)	1008(1367)	1119(1290)	0.598
Calcification Number	18.0(17.9)	25.6(18.9)	0.010
Aneurysmal Wall Surface (mm ²)	25149(10290)	24541(8512)	0.684
Calcification Euler Distance (mm)	71.5(34.1)	80.7(26.6)	0.059

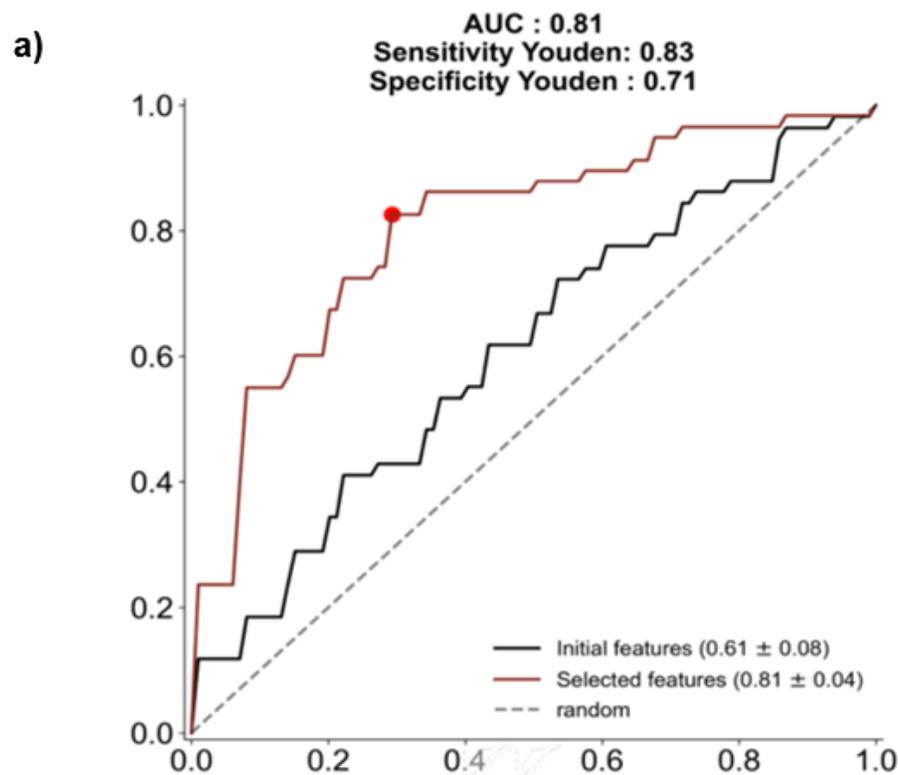
III. Results (Machine learning)

Figure 3 -

a) ROC-curves for rupture status classification

Black line is the ROC curve for rupture status prediction using ExtraTrees classifier on all initial variables (AUC 0.61 ± 0.08)

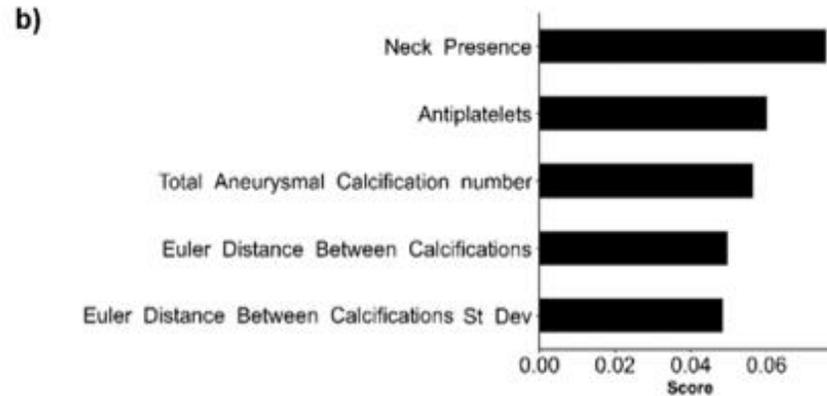
Red line is the ROC curve for rupture status prediction using XGBoost classifier on the 5-variable reduced dataset (0.81 ± 0.04)



III. Results (Machine learning)

Figure 3 -

b) Relative importance of 5-variable reduced dataset from XGBoost classifier



IV. Conclusion

- For a given calcification volume, AAAs with a larger number of well-distributed calcification clusters are less likely to rupture (equivalent calcification volume in both groups but increased number of calcifications in non-ruptured)
- A model including AAA calcifications better predicts rupture compared to a model based solely on DMax and sex alone.
 - **Our 5-variable machine learning model:** AUC 0.81 ± 0.02 (83% sensitivity and 71% specificity)
 - **Tang et al. sex and diameter model:** AUC 0.67 (95% CI, 0.58-0.77%) (60% sensitivity and 77% specificity)
- The 5 top variables chosen by ExtraTrees classifier correspond to the variables that had the highest p-values in the univariate analysis
- Although 3/5 of top machine learning variables are related to calcifications, aneurysmal neck and anticoagulation might have an important role in AAA rupture.

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