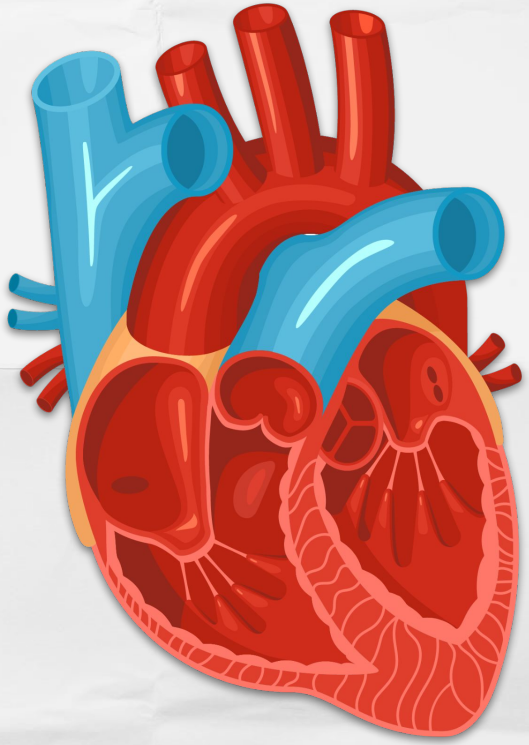
Universitat Pompeu Fabra Barcelona

SANT PAU Campus Salut Barcelona

Hospital de la Santa Creu i Sant Pau

Stenosis Quantification & Visual Analytics for CAD Diagnosis



Adrià Cortés Cugat

Mathematical Engineering in Data Science

PhySense Update 1

Context, Focus & Future Possibilities

Current Focus

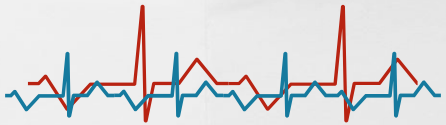
To ensure project feasibility, I am focusing the initial phase of the TFG entirely on ***Stenosis Quantification***.

Final Goal

Automate manual feature extraction to provide clinicians with a pre-assessed **"good starting point"**, significantly **saving time** in CAD diagnosis (Acebes, 2023 [1]).

Future Pathways → Open to Exploration After MVP

- **Plaque Quantification:** Utilizing ML/Classification models to flag High-Risk Plaque.
- **Visualization:** Investigate about complex tools like CMPR (Curved Multiplanar Reformation).
- **Integration:** Finalizing the data link to the automated Reporting Platform (Ferrer, 2024 [2]).



Contextual Information

The "Input" Layer (Maren Clapers, 2025 [3])

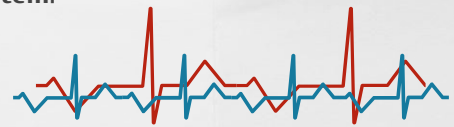
- **Maren's Work:** Segmentation and Labeling of the coronary artery trees.
- **My Starting Point:** Pre-processed **centerline** data, including **coordinates (Px, Py, Pz)** and **Label ID**.

The Algorithmic Baseline (Ela Burrull, 2024 [4])

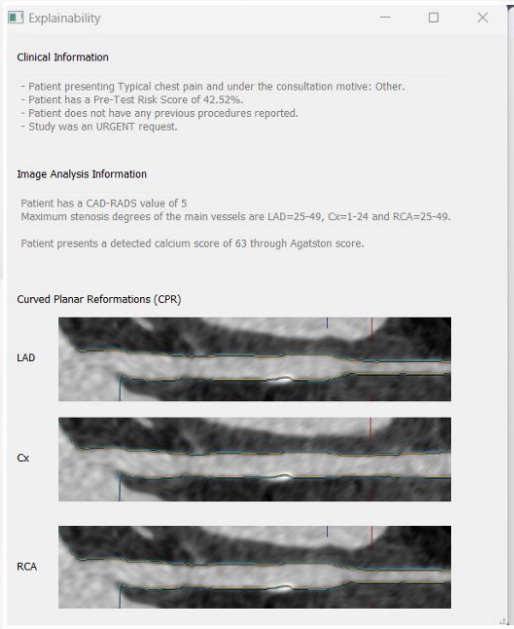
- **Ela's Work:** The core geometric formula for calculating Percentage Diameter Stenosis.
- My Task: Implement, validate, and define this algorithm for clinical reliability and visualization.

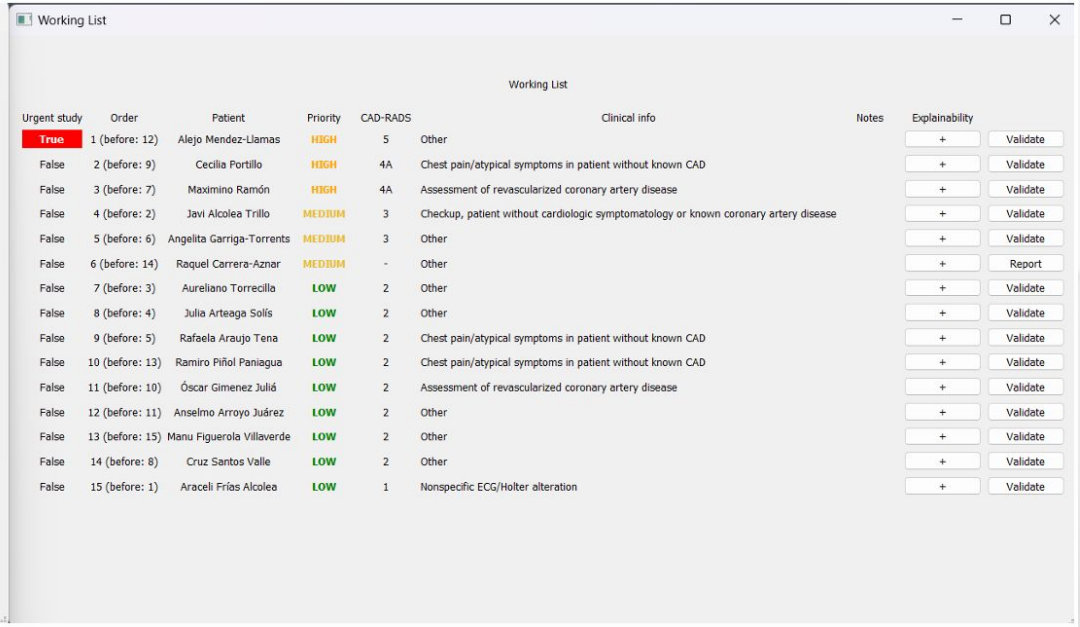
The "Output" Target (Ferrer, 2024 [2])

- Use my quantified results (**Max %DS**) to derive the final **CAD-RADS Score** and adapt them to be the input of Eva's **Prioritization and Explainability System**.



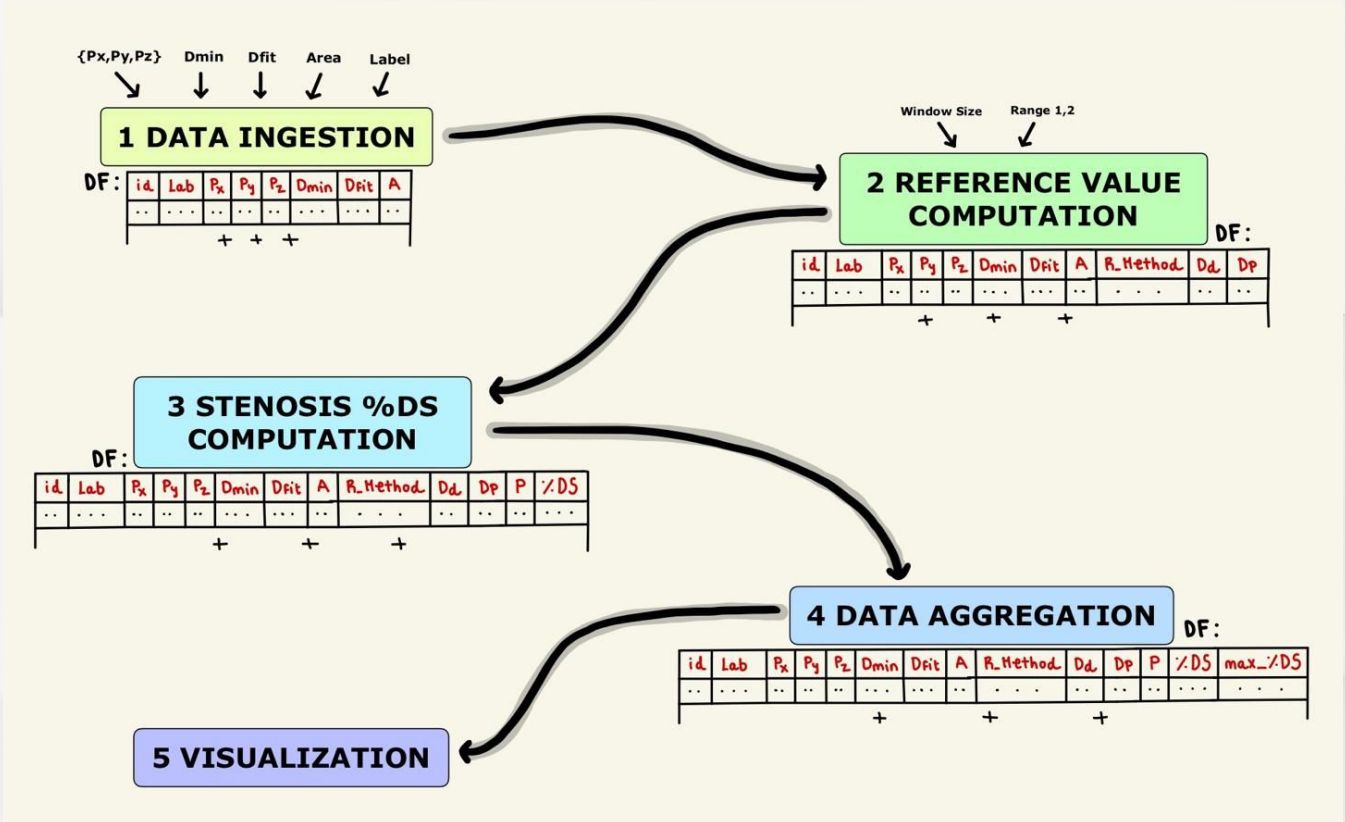
Contextual Information





Acebes, 2023 [1] & Ferrer, 2024 [2]

Stenosis Quantification Generalized Pipeline



Designed a pipeline leveraging the mathematical framework established by **Burrull [4]** to bridge the gap between **raw geometric data** and **clinical visualization**.

This **5-step workflow** illustrates the sequential transformations required to convert **raw centerline coordinates** into an **interactive visual analytics tool**.

Stenosis Quantification Pipeline I

Assumptions

- All input information is available and has the correct format.
- Ela's methodology to obtain reference values and %DS is consistent and reliable.
- The "hyperparameters" given to compute the reference values are optimal for %DS computation.

1.Data Ingestion

- **Input:**
  - **{Px,Py,Pz}:** Point P coordinates.
  - **Dmin:** Diameter of the best fit circle in point P.
  - **Dfit:** Diameter of the inscribing circle in point P.
  - **Area:** Sectional Area in point P.
- **Output: Python DataFrame I**

What To Do?
Read input data of centerline properties for an artery or vessel segment points and build a dataframe to store the information.

2.Reference Value Computation

- **Input: Python DataFrame I, Window Size, Range 1 and Range 2**
- **Output: Python DataFrame II**

What To Do?
From the previous structured DF, compute both reference values for each point/row:
- Dd: Distal Reference Value
- Dp: Proximal Reference Value

Using 2 different methods from Ela's work:
- Method 1: Value
- Method 2: Range

This would produce a triplet for each DF point/row defined as: (Dd, Dp, Value) & (Dd, Dp, Range).

Transform the input DataFrame by adding these new computed values for each point/row.

3. Stenosis %DS Computation

- **Input: Python DataFrame II**
- **Output: Python DataFrame III**

What To Do?
From thr previous DF information, compute the %DS for every point/row using Ela's formula, and using each possible value for variable p:

$$DS\% = \left(1 - \frac{P}{\left(\frac{dp + dd}{2}\right)}\right) \times 100$$

p = {**Dmin**, Dfit, Area}

Transform the input DataFrame by adding the p value used and the new computed value for each point/row.

Universitat Pompeu Fabra Barcelona

SANT PAU Campus Salut Barcelona

Hospital de la Santa Creu i Sant Pau

Stenosis Quantification Pipeline II

4.Data Aggregation

- **Input: Python DataFrame I**
- **Output: Python DataFrame IV**

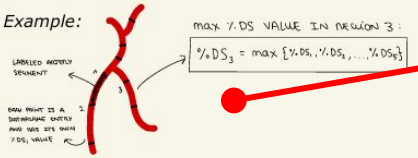
What To Do?
Each DataFrame row represents a point and its behavior in a certain region of an artery.

Given vessel labels, points can be splitted by regions. Transform the DF by adding the label region of the artery for each point/row and adding the following new feature that shows the maximum %DS whithin a range of labeled artery points:

for each point/row with same label and artery_id:

$$max\_\%DS = max\{point(i).\%DS, max\_\%DS\}$$

Since there are several values of %DS for each point depending on (p and method used to compute reference values Dd and Dp), there will also be several values for the previous maximum within each label range.



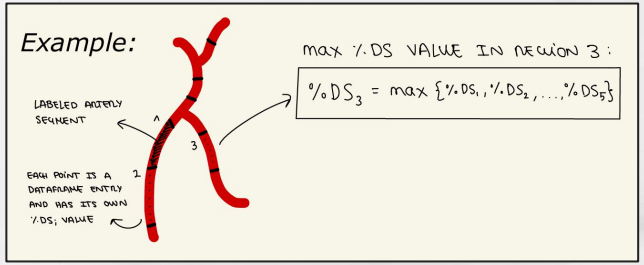
This can be useful to later visualize which labeled sectors of the artery have more stenosis risk.

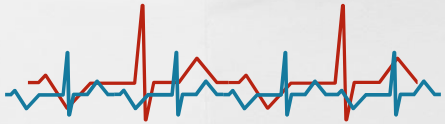
5. Visualization

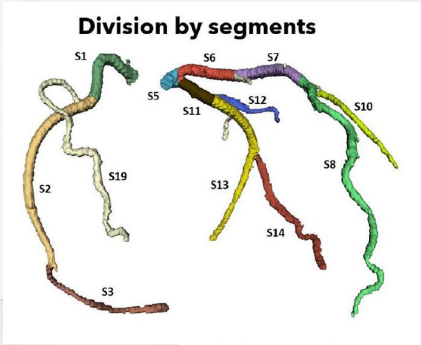
- **Input: Python DataFrame IV**
- **Output: Python Non-Interactive & Interactive Visualizations**

What To Do?
Use all the initial data of the coronary artery and the computed metrics for each point and regions to create several different visualizations to facilitate the process of analyzing the stenosis at certain region.

I am currently investigating which visual representations could be meaninfgull for the results representation of the given task.







Label correctly using topological rules

- Segment 1: pRCA
- Segment 2: mRCA
- Segment 3: dRCA
- Segment 4: R-PDA
- Segment 5: LM
- Segment 6: pLAD
- Segment 7: mLAD
- Segment 8: dLAD
- Segment 9: D1
- Segment 10: D2
- Segment 11: pCx
- Segment 12: OM1
- Segment 13: LCx
- Segment 14: OM2
- Segment 16: R-PLB
- Segment 17: RI
- Segment 19: tertiary

Acebes, 2023 [1]

Algorithmic Validation - Experiments

Experiment 1: Synthetic Data Generation

Generate data with known truth lesions to tune hyperparameters before facing clinical data. Create simple geometric models (straight/curved) segments and inject known lesions to use them as input data for the pipeline.

Experiment 2: D_ref Method Tuning

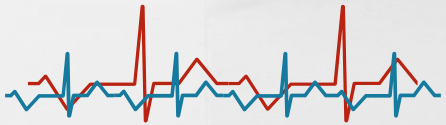
Tune parameters for *"Range Method"* (Window Size, Range 1,2) and compare results against the simpler *"Value Method"* (Fixed Offset).

- **Goal:** Try to select the most stable and robust method for calculating the reference diameter that is used then to compute diameter stenosis percentage.

Experiment 3: Metric Comparison

Compare final results using Dmin vs. Dfit vs. Area as the calculation parameter p for %DS.

- **Goal:** Determine the most accurate metric that correlates with expected clinical severity.



ML/DL Opportunities for Quantification

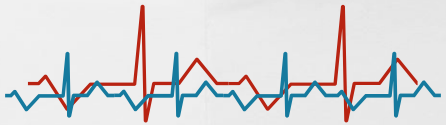
Once the algorithmic baseline is validated, the natural progression is moving to ML/DL to overcome geometric limitations and enhance robustness.

ML/DL Advantage (Zhang et al., 2024 [5])

- ML/DL methods outperform traditional algorithms by **eliminating the need for manual feature engineering**. They automatically process large datasets and model complex, non-linear interactions with high fidelity, leading to more robust stenosis detection.

Deep Learning Potential (Hong et al., 2024 [6])

- Deep Learning (CNNs) achieved **highly accurate quantitative stenosis measurement** (r=0.957 correlation with experts). The models bypass manual, subjective geometric steps (like D_ref selection) by **learning intrinsic features directly from the image data.**
- **Further Work:** Investigate the features and architectures used in these papers to try to apply them to our quantified data or as a direct classification model (Predict CAD-RADS vs. Predict %DS).



Bibliography: References

[1] **Acebes, C.** (2023). *An Artificial Intelligence Framework for the Prioritization and Reporting of Coronary Artery Disease Patients in a Radiology Department.* (Unpublished master's thesis). Universitat Pompeu Fabra.

[2] **Ferrer, E.** (2024). *Enhanced Prioritization and Reporting for Coronary Artery Disease Diagnosis.* (Unpublished bachelor's thesis). Universitat Pompeu Fabra.

[3] **Clapers, M.** (2025). *Automatic Labeling of Coronary Artery Segments: Multi-Strategy Development and Evaluation.* (Unpublished bachelor's thesis). Universitat Pompeu Fabra.

[4] **Burrull, E.** (2024). *Stenosis Quantification Pipeline.* (Unpublished bachelor's thesis). Universitat Pompeu Fabra.

[5] **Zhang, X., Zhang, B., & Zhang, F.** (2024). *Stenosis detection and quantification of coronary artery using machine learning and deep learning. Angiology, 75(5), 405-416.* https://journals.sagepub.com/doi/full/10.1177/00033197231187063?casa_token=IKb0AufrpGoAAAAA%3AZa-jD90HZCfXH2ELY30TTZl2Ni1WiINI9fodN1WjyhY-xBk4ijB8I0XTT8c7bvXeXntngpmwli94bQ

[6] **Hong, Y., Commandeur, F., Cadet, S., Goeller, M., Doris, M. K., Chen, X., ... & Dey, D.** (2019, March). *Deep learning-based stenosis quantification from coronary CT angiography. In Proceedings of Spie--the International Society for Optical Engineering (Vol. 10949, p. 109492I).* https://pmc.ncbi.nlm.nih.gov/articles/PMC6874408/

upf. Universitat Pompeu Fabra Barcelona

SANT PAU Campus Salut Barcelona

Hospital de la Santa Creu i Sant Pau