# Evaluating Different Explainability Methods for Coronary Artery Segmentation

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## Professional Experience

PhD candidate in Knowledge Graphs and Explainable AI at the School of Informatics, Aristotle University of Thessaloniki. Diploma in Electrical & Computer Engineering (2020) and MSc in Advanced Computer & Communication Systems (2023). As a researcher at CERTH, actively involved in five EU-funded research projects, working on AI, knowledge graphs, and explainable systems with real-world impact. Contributed on more than 9 conference or journal publications.

# Background and Motivation

- **Cardiovascular Diseases** remain the leading cause of mortality worldwide.

- **X-ray Coronary Angiography** is the gold standard for visualizing the coronary vasculature, however manual interpretation is:
  1. Labor-intensive,
  2. Subjective,
  3. Prone to inter-observer variability.

- **Automated vessel segmentation** can accelerate clinical workflows and provide consistent anatomical delineation.

# Related Work

- **Explainable Artificial Intelligence (XAI) in medical imaging** is widely used for **different tasks**, such as Coronary Artery Disease diagnosis, Electrocardiogram analysis and chest X-ray interpretation. [1]

- The **most commonly** used XAI methods are **Grad-CAM, LIME, SHAP and RISE.** [2]

- Deep learning models have achieved **high accuracy in Coronary Artery Segmentation**, but XAI methods are **rarely integrated**. [3]

- **Quantitative evaluation of explanations**, particularly for segmentation tasks involving thin, branching structures like coronary arteries, **remains underexplored**. [4]

[1] T. Do, P. Huynh, M. Nguyen, and V. Nguyen,"An XAI-based deep learning framework for coronary artery disease diagnosis using SPECT MPI polar map images," in Proc.Seventh Int. Conf. Res. Intell. Comput. Eng., 2022, pp. 235–241,doi: 10.15439/2022R06.
[2] M. Goettling, J. M. Schwenk, F. Kragness, J. Tomaszewski, and R. F. Speier, "xECGArch: A trustworthy deep learning architecture for interpretable ECG analysis considering short- term and long-term features," Sci. Rep., vol. 14, no. 13122, 2024.
[3] H. S. Anand, R. K. Sharma, and P. Gupta, "Coronary vessel segmentation in X-ray using U-Net," in Lecture Notes in Networks and Systems, vol. 969, Springer, 2024, pp. 57–66.
[4] M. T. Ribeiro, S. Singh, and C. Guestrin, "'Why should I trust you?' Explaining the predictions of any classifier," in Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min., 2016, pp. 1135–1144.

# Main Contribution of This Study

- Utilize a benchmark of **five XAI methods,** Grad-CAM, Grad-CAM++, Score-CAM, LIME and Integrated Gradients, on coronary angiography images from the **ARCADE** dataset.

- Introduce a **vessel-aware evaluation framework** with **four metrics,** Pointing Game (PG), Average Precision (AP), Intersection over Union (IoU) and Energy Concentration Ratio (ECR).

- Optimize **layer selection & scoring** for each method, providing better understanding for the explainability results.

# Dataset Acquisition and Preprocessing

- This study employs data from the **ARCADE** dataset which contains **1,200 X-ray Coronary Angiography images** with pixel-level **vessel annotations**.

- **Each image** is accompanied by a **binary mask** labeling vessel vs. background.

- While ARCADE provides region-specific annotations for 26 SYNTAX anatomical regions, **this study focuses on binary segmentation** to isolate the vessel tree as a whole.

- **Its size, annotation quality, and task diversity** make this dataset particularly **suitable** for robust Coronary Artery Segmentation and XAI evaluation.

- **Three preprocessing** techniques were applied to the images, White Top Hat filter, Normalization and Contrast Limited Adaptive Histogram Equalization (CLAHE).

# Model Architecture and Training Configuration

- The segmentation architecture that was selected is based on the **U-Net** model because it provided the **best trade-off between segmentation performance and interpretability.**

- The network is comprised of **five encoder and five decoder** stages **with skip connections**, in order to preserve spatial detail in coronary vessels.

- During training, a **Centerline Cross-Entropy loss** was employed to emphasize accurate segmentation of thin and elongated coronary vessels.

# Model Performance Evaluation

- The **metrics** that were used to evaluate the **performance of the model**:
  1. **Precision**, the number of true positive results divided by the number of all positive results.
  2. **Recall**, the number of true positive results divided by the number of all cases that should have been identified as positive; in this case it measures how many true vessel pixels are successfully identified, reflecting the ability to capture thin and peripheral branches.
  3. **Dice Coefficient**, quantifies the overlap between the predicted and ground truth masks by balancing precision and recall. It is widely used in medical segmentation benchmarks.
  4. **Intersection over Union**, measures the ratio of the intersection area to the union area between prediction and ground truth.

# Explainability Methods

- The XAI methods that were tested are the following:
  - Gradient-based:
    - ➤ Gradient-weighted Class Activation Mapping (**Grad-CAM**),
    - ➤ **Grad-CAM++,**

  - Perturbation-based:
    - ➤ Score-CAM,
    - ➤ Local Interpretable Model-agnostic Explanations (**LIME**),

  - Attribution-based:
    - ➤ Integrated Gradients (**IG**).

# Explanations Performance Evaluation

- The **metrics** for evaluating the **performance of the explanations**:
  1. **Pointing Game (PG)** measures localization accuracy by testing whether the regions of highest attention overlap with true vessel structures.
  2. **Average Precision (AP)** evaluates the ranking ability of heatmap values under class imbalance, since vessels occupy only a small fraction of the image.
  3. **Intersection over Union (IoU)** quantifies the overlap between binarized attention maps and vessel structures.
  4. **Energy Concentration Ratio (ECR)** measures how much of the explanation energy is concentrated within vessels compared to background regions.

# Model Performance Results

- **Different tests** were performed to evaluate the performance of the model. Each test **assessed the effect of preprocessing and post-processing** on segmentation accuracy:
  - **Test 1**: No Modifications
  - **Test 2**: Post Processing
  - **Test 3**: Filtering
  - **Test 4**: Post Processing with Filtering

| Metrics | TEST 1 | TEST 2 | TEST 3 | TEST 4 |
|---------|--------|--------|--------|--------|
| Dice | 0.653 | 0.653 | 0.677 | **0.679** |
| IoU | 0.484 | 0.485 | 0.512 | **0.514** |
| Precision | 0.712 | 0.712 | 0.720 | **0.721** |
| Recall | 0.603 | 0.604 | 0.640 | **0.642** |

# Explanations Performance Results for patient 15

- For Grad-CAM, Grad-CAM++ and Score-CAM **a random number of layers** were tested to find for which one each method performs the best.

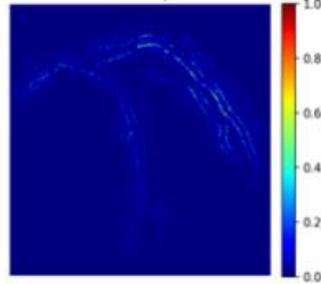- The **Score** value is the average of all the other values.

| Method | PG | AP | IoU | ECR | Score |
|---|---|---|---|---|---|
| Grad-CAM | **0.286** | **0.580** | **0.188** | **0.465** | **0.380** |
| Grad-CAM++ | **0.286** | **0.580** | **0.188** | **0.465** | **0.380** |
| Score-CAM | 0.200 | 0.416 | 0.143 | 0.283 | 0.260 |
| IG | 0.145 | 0.059 | 0.067 | 0.068 | 0.085 |
| LIME | 0.064 | 0.061 | 0.040 | 0.186 | 0.088 |

# Example: Explanation Heatmaps for prediction for patient 15
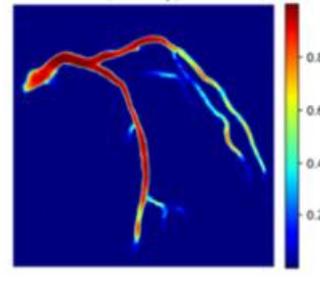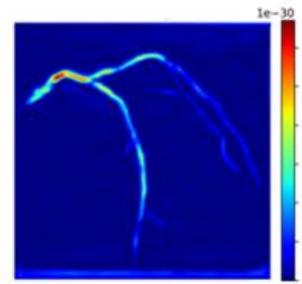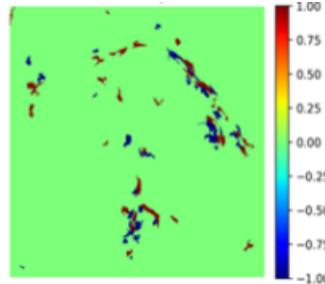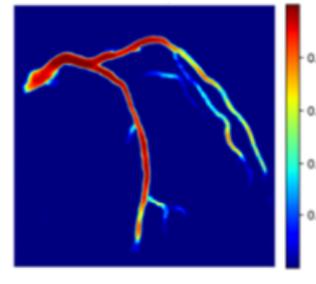
# Conclusions

- A **systematic evaluation methodology** for XAI in coronary artery segmentation is proposed, using the ARCADE dataset and a U-Net backbone.

- **Grad-CAM and Grad-CAM++ produced the most clinically meaningful explanations**, consistently aligning with coronary vessel centerlines.

- **Score-CAM achieved moderate localization**, while **IG and LIME failed to capture vessel continuity**, performing poorly on vessel-aware metrics.

- The results demonstrate that **multi-metric evaluation is essential** to reveal complementary strengths and failure modes of XAI methods in medical imaging.

# Future Work

- Extend the framework to **advanced architectures** (e.g., TransUNet, nnU-Net).

- Evaluate on **larger and more diverse datasets**.

- Incorporate **additional XAI methods** and **expert cardiologist validation**.

- Investigate whether XAI can reveal **clinically relevant structures missed by annotations**.

- Move toward **real-time, clinically integrated explainability**.

# THANK YOU!