# Automatic Contrast Phase Detection on Abdominal Computed Tomography using **Clinically-Inspired Techniques**

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**1. Introduction:** Abdominal computed tomography (CT) scans are commonly utilized to assess internal organs and structures. CT exams can be performed by scanning subjects in different con- ditions (phases) related to the use of intravascular contrast agents, which enhance the radiodensity of blood vessels and vascularized internal organs. Accurate determination of phase is crucial, especially as the quantification of biomarkers in the rapidly emerging field of opportunistic imaging relies on it. (Pickhardt et al., 2013)

We present the Contrast Phase algorithm, which identifies four contrast phases: non-contrast, arterial, venous, and delayed. This pipeline is design to read most commonimage formats (DICOM and NIFTI), segment relevant organs, and classify contrast phases. It is made publicly available at https://github.com/ <u>StanfordMIMI/Comp2Comp</u> (Blankemeier et al., 2023).

#### 2. Methods

The data acquisition and labeling process for this study involved obtaining 739 abdominal CT exams from 238 unique patients. 1545 axial series were split into the training set, containing 1183 examples, and the test set, containing 362 examples.

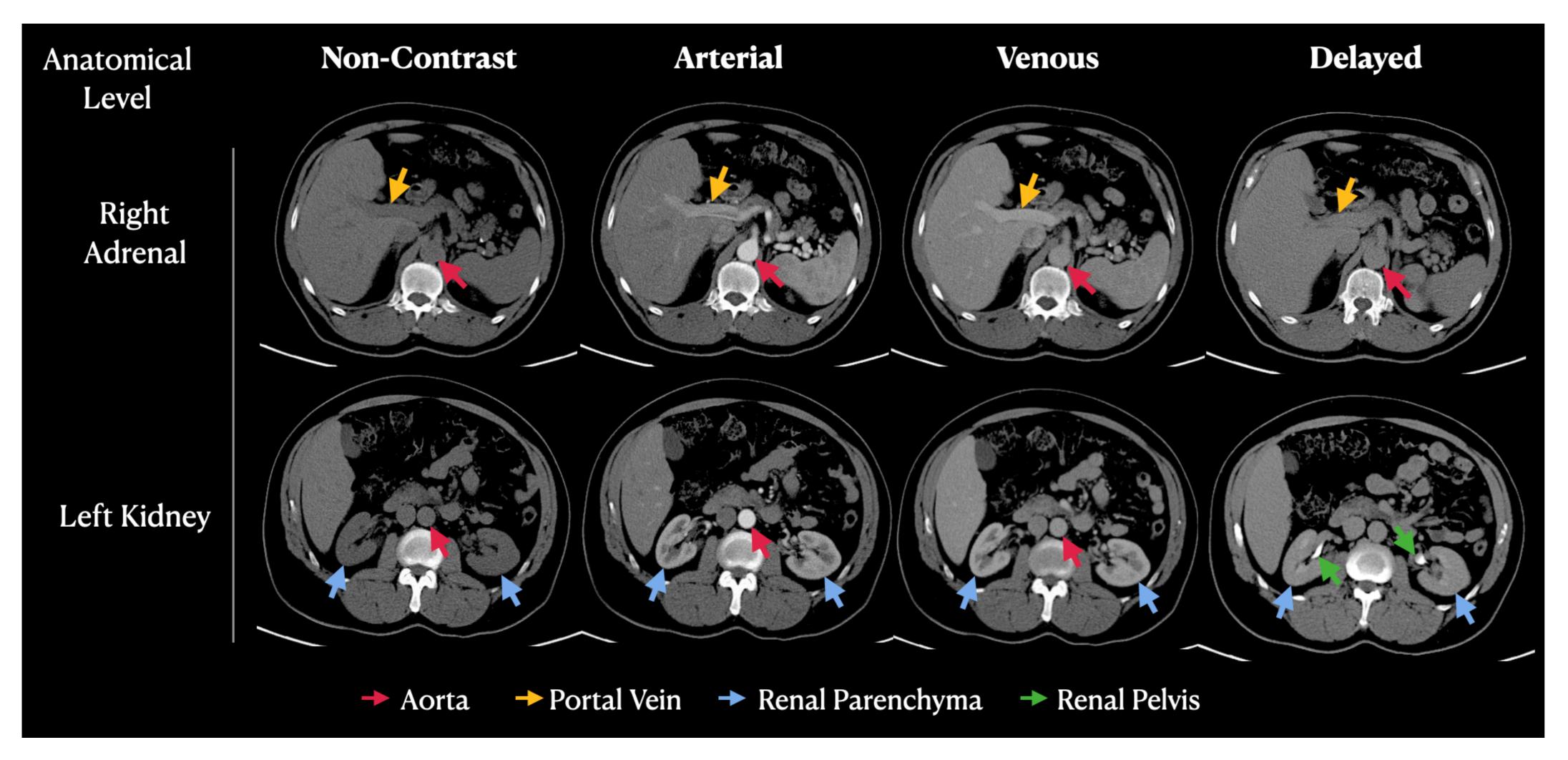


Figure 1: Example abdominal CT images at the anatomical level of the right adrenal gland and the left kidney, representing each of the four classes. Observe the variations in pixel intensity across the phases in the key structures: aorta (red arrows), portal vein (yellow arrows), renal parenchyma (blue arrows), and renal pelvis (green arrows).

#### References

3. Jakob Wasserthal, Manfred Meyer, Hanns-Christian Breit, Joshy Cyriac, Shan Yang, and Martin Segeroth. Totalsegmentator: robust segmentation of 104 anatomical structures in ct images. arXiv preprint arXiv:2208.05868, 2022.

We ensured that each patient's data was exclusively allocated to either the training or the test set.

**Segmentation of Organs:** The first stage involves the segmentation of key anatomical structures, including the aorta, inferior vena cava, portal vein, renal parenchyma, and renal pelvis, using Total Segmentator, a deep learning-based open-source segmentation tool (Wasserthal et al., 2022).

**Feature Extraction:** After segmentation, we computed quantitative 48 low-level radiomics features that characterize the radiointensity statistics from the aforementioned anatomical structures.

**Classification:** Extreme Gradient Boosting (XGBoost) (Chen and Guestrin, 2016) was trained on the extracted features to classify the CT images into the four distinct contrast phases.

### 3. Results and Discussion

The classifier demonstrated high accuracy on the test set in identifying the four contrast phases, with an accuracy of 92.3% and F1-scores of 96.6% for non-contrast, 78.9% for arterial, 92.2% for venous, and 95.0% for delayed phase, as shown in Table 3. These results highlight that using segmentations of clinically relevant anatomic structures can contribute to the development of an accurate contrast phase classifier.

The algorithm has been made publicly available through the Comp2Comp Inference Pipeline - Open-Source Body Composition Assessment on Computed Tomography on the following GitHub repository: <u>https://github.com/StanfordMIMI/Comp2Comp</u>. We provide an easy-to-use command line interface that operates on DICOM and NITI medical image formats.

Metric	Non-Contrast	Arterial	Venous	Delayed
# Training examples	285 (24.0%)	49 (4.1%)	503 (42.5%)	346 (29.2%)
# Test examples	76 (20.9%)	22 (6.0%)	139 (38.4%)	125 (34.5%)
Precision	100.0	93.7	87.1	97.4
Recall	93.4	68.1	97.8	92.8
Specificity	100.0	99.7	91.0	91.0
F1 score	96.6	78.9	92.2	95.0

Table 1: Performance metrics and dataset distribution for the classification model



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