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Purpose

To assess the efficacy of deep convolutional neural networks (DCNNs) in differentiating acute aortic dissections from non-dissected aortas on thoracic CT



dissection⁵

Introduction

- Acute thoracic aortic dissection represents the deadliest iteration of the acute aortic syndrome, with an estimated annual global incidence of 30 million cases per year and a 90% mortality rate without emergent treatment¹
 - Lethal complications of cardiac tamponade, aortic rupture, congestive heart failure, stroke, and myocardial infarction²
 - Malperfusion syndrome complications of paraplegia, acute renal failure, and mesenteric ischemia²
- Stanford Type A dissections represent 61% of cases and emerge proximally to the left subclavian artery³
- Stanford Type B dissections represent 39% of cases and occur distally to the left subclavian artery³
- Aortic dissections must be managed emergently with aggressive blood pressure stabilization, open surgical repair, or thoracic aortic endograft placement⁴
- Thoracic CTA is the most frequent modality employed in the primary diagnosis of aortic dissection, and is utilized in 69% of all cases⁶
- Prior semi-automated solutions for detection algorithms on CTA achieved modest success
 - Semi-automated algorithm to detect healthy, non-dissected ascending aortas with an accuracy of 97%, with no information regarding presence of aortic pathology⁸
 - Wavelet analysis and probabilistic model segmenting true and false lumens in Stanford Type A aortic dissections, with modest results of a sensitivity 0.7 and a specificity of 0.89
 - Proposed CAD solution specifically designed to segment dissected aortas on 3D CTA with no real world performance data¹⁰
- Deep convolutional neural networks (DCNNs) have already demonstrated success with regard to image classification solutions on CTA
 - Successful classification and segmentation of coronary arteries on CTA with plaque burden scoring¹³
 - Bicuspid aortopathy classification on CTA¹⁴
 - Successfully prediction of 30-day mortality following interventions for Stanford Type A dissections¹⁵
- Radiologists are responsible for the emergent diagnosis of aortic dissections on thoracic CTA to ensure timely treatment and intervention
- A computer-aided detection (CAD) system that could automate instantaneous detection of critical aortic dissections to triage patient care appropriately would therefore be invaluable.

Automated Assessment of Acute Aortic Dissection on Thoracic CT Using Deep Learning

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Figure 2 ROC Curve: Inception V3 DCNN

Methods

- 80 de-identified HIPAA compliant CT chest examinations were obtained on unique patients • 50% of studies demonstrated acute aortic dissection (40/80)
 - 50% of studies comprised control studies without dissection (40/80)
- Studies were verified by two board-certified radiologists
- The Inception V3 DCNN was used using the Tensorflow framework, pretrained on 1.2 million everyday color images
- Real-time data-augmentation was performed
 - Colorization, rotations, translation, shearing, and zoom
- Six window-level settings were used for each slice.
- Data were split into the following datasets:
 - Training: 30 patients, 15 with and 15 without dissection; 4235 images
 - Validation: 10 patients, 5 with and 5 without dissection; 1295 images
 - Test: 40 patients, 20 with and 20 without dissection; 3423 images
- A 2D network was used that analyzed three slices at a time
- Receiver operating characteristic (ROC), area-under-the-curves (AUC) on the test data, and sensitivity and specificity of the algorithms were performed

Results

- Test dataset results for binary algorithm distinguishing aortic dissection from controls:
 - Patient-level AUC of 0.97 (95% CI: 0.91-1.00)
 - Sensitivity of 100.0% (20/20)
- Two false positive cases with eccentric mural thrombus and endovascular stent



Figure 3 Stanford Type B aortic dissection axial CTA with colorized augmentation (left) and corresponding Class Activation Map¹⁶ (CAM) (right)

aortas on thoracic CTA with an AUC of 0.97



Figure 5 False positive: Endovascular stent axial CTA with colorized image (left) and corresponding CAM (right)

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Conclusion

DCNNs demonstrate success in the classification of acute aortic dissection from non-dissected

Automated, instantaneous classification of critical aortic dissections could allow radiologists to expediently diagnose aortic dissections and ensure timely intervention

Figure 4 False positive: Eccentric thrombus axial CTA with colorized image (left) and corresponding CAM (right)

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