Heart Surgery Forum 2025; 28(8): E644–E655
doi: 10.59958/hsf.8381 https://journal.hsforum.com/

Review

Advancements in Computed Tomography Analysis for Thoracic Aortic Surgery: The Expanding Role of Automation

Devina Chatterjee[1], Sangmita Singh[2], Benjamin L. Shou[3,*]

[1]Department of Cardiothoracic Surgery, University of Maryland School of Medicine, Baltimore, MD 21201, USA
[2]Department of Biomedical Engineering, Johns Hopkins University, Baltimore, MD 21218, USA
[3]Department of Cardiothoracic Surgery, Stanford University, Palo Alto, CA 94304, USA
*Correspondence: bshou1@stanford.edu (Benjamin L. Shou)

Submitted: 5 January 2025 Revised: 26 March 2025 Accepted: 26 May 2025 Published: 26 August 2025

Abstract

Computed tomography (CT) is crucial for evaluating complex aortic anatomy, facilitating surgical planning, and improving patient outcomes in thoracic aortic surgery. Recent advancements in artificial intelligence (AI)-driven tools offer potential improvements in diagnostic accuracy and interventional planning through automated segmentation and feature extraction. We conducted a systematic review of AI-based tools for aortic CT imaging, focusing on machine learning and deep learning algorithms used in segmentation and feature extraction. Databases searched included PubMed, Embase, and IEEE Xplore, using terms such as "Thoracic Aortic Surgery", "CT Imaging", "Segmentation", and "Outcome Prediction". This review identified high-performance segmentation models, including U-Net and convolutional neural network (CNN) architectures. Radiomic analyses and automated features demonstrated correlations with surgical outcomes, such as aneurysm growth rates and thrombus assessment. AI-driven automation in CT imaging is an expanding field with potential to improve diagnosis, operative planning, and prognostication in aortic pathologies. Further refinement and integration of these tools in clinical practice could improve diagnostics and management for patients with thoracic aortic disease.

Keywords

cardiac surgery; angiography; computed tomography; AI (artificial intelligence); aneurysm; aortic; endovascular techniques; algorithms

Introduction

Medical imaging is a crucial tool in evaluating and managing various cardiac pathologies, particularly in diagnosis, surgical planning, and post-treatment follow-up. Computed tomography (CT) has emerged as the cornerstone modality for assessing aortic anatomy and diagnosing acute aortic syndromes, aneurysms, chronic dissections, and congenital malformations [1–4]. High-quality CT imaging can also provide detailed visualizations, allowing surgeons to precisely measure dimensions, detect calcifications, determine morphology of intraluminal flaps, and assess involvement of branch vessels, all of which are crucial for preoperative planning and intraoperative guidance [5].

Both the American College of Cardiology (ACC)/American Heart Association (AHA) and the European Society of Cardiology (ESC) guidelines highlight the use of CT in the management of thoracic aortic disease [5–7]. The ACC/AHA recommends computed tomography angiography (CTA) as the first-line imaging modality for patients with acute aortic syndrome to confirm diagnoses such as aortic dissection or intramural hematoma [5,6]. Similarly, ESC guidelines also emphasize the role of preoperative CTA in managing thoracic aortic aneurysms, not only in evaluating size, morphology, and calcifications, but also in surgical planning for traditional open surgery or endovascular aortic repair (EVAR) [7].

Automation has significantly expanded the diagnostic capabilities of three-dimensional (3D) imaging. Machine learning (ML) and artificial intelligence (AI) techniques have been widely implemented in medical imaging, primarily in data processing methods that convert detector-level electronic signals into viewable grayscale images on a workstation [8,9]. These methods are crucial for precise and timely analysis of images, but are often proprietary and occur in the backend with minimal end-user input. The modern AI era has driven new interest in automated or semi-automated tools that directly influence physician interpretation of imaging [3,10].

Aortic disease serves as a prime target for new imaging AI technologies, given the relatively large caliber and pathology of the aorta, which most commonly manifests as changes in size, wall thickness, or morphology [10]. This review aimed to provide an overview and analysis of AI-driven CT imaging techniques for thoracic aortic surgery, focusing on their applications in surgical planning, risk stratification, and prediction of patient outcomes.

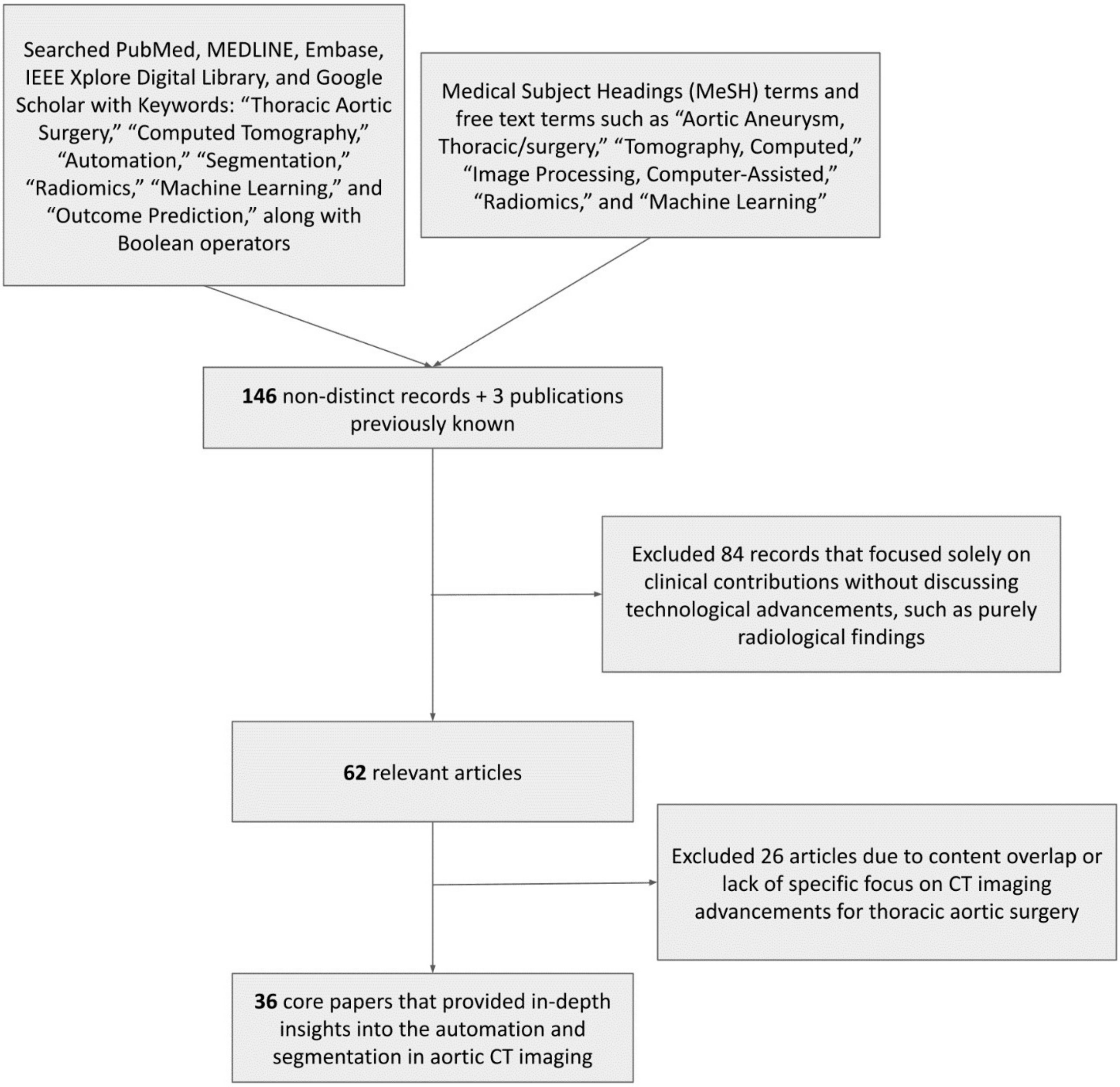

Fig. 1. Flowchart of the literature search methodology and inclusion/exclusion criteria. CT, computed tomography.

Manuscript Outline

This review examined state-of-the-art and clinically relevant methods for analyzing aortic CT imaging, including ML and deep learning algorithms for segmentation, established feature extraction, and novel feature discovery (Table 1, Ref. [11–26]). We will describe and evaluate software and packages that exist to automatically or semi-automatically analyze the thoracic aorta (Table 2, Ref. [2,3,27–42]). Finally, this review will consolidate best practices and explore specific contexts in which radiomics is integrated into these automated tools to enhance clinical utility (Table 3, Ref. [27,43–48]).

Search Criteria

We performed a comprehensive search across multiple databases to gather relevant literature on advancements in CT analysis for thoracic aortic surgery with a focus on automation (Fig. 1). The databases searched included PubMed, MEDLINE, Embase, IEEE Xplore Digital Library, and Google Scholar. We used a combination of core keywords such as “Thoracic Aortic Surgery”, “Computed Tomography”, “Automation”, “Segmentation”, “Radiomics”, “Machine Learning”, and “Outcome Prediction”, along with Boolean operators to refine our results. For instance, our query structure included terms such as

("Thoracic Aortic Surgery" AND "Computed Tomography" AND "Automation") OR ("CT Imaging" AND "Segmentation" AND "Outcome Prediction").

Additionally, we employed Medical Subject Headings (MeSH) terms and free text terms such as "Aortic Aneurysm, Thoracic/surgery", "Tomography, Computed", "Image Processing, Computer-Assisted", "Radiomics", and "Machine Learning" to further narrow down the search. During this process, we initially retrieved 146 non-distinct records. We also considered three papers already known to us due to their significance in the field.

After screening the titles and abstracts, we excluded records that focused solely on clinical contributions without discussing technological advancements, such as purely radiological findings. This screening process reduced the number of relevant papers to 62 distinct articles. We further assessed these articles and excluded 26 due to content overlap or lack of specific focus on CT imaging advancements for thoracic aortic surgery. Ultimately, we identified 36 core papers that provided in-depth insights into the automation and segmentation in aortic CT imaging.

These papers were selected based on their recent contributions in their respective areas. To our knowledge, this review provides a comprehensive analysis of published studies on advancements in CT imaging for thoracic aortic surgery, with a particular emphasis on the role of automation.

Overview of Automated Segmentation and Feature Extraction Techniques

Automated segmentation techniques utilize ML and deep learning models to identify and separate regions of interest within complex datasets [49,50]. The advent of convolutional neural networks (CNNs) and U-Net architectures has significantly improved the ability to perform efficient segmentation, enabling detailed analysis of medical images, such as CT and magnetic resonance imaging (MRI) scans [51,52]. Tools, including automatic thresholding, edge detection, and region growing, are commonly used to enhance the segmentation accuracy, providing clinicians with precise and reliable data for diagnosis and treatment planning [52]. Table 1 provides a comprehensive overview of various automation techniques and tools specifically utilized for CT imaging segmentation of the thoracic aorta. Specific computer-aided methods include, but are not limited to:

- CNNs: used for their exceptional ability to learn and generalize features from large imaging datasets [11–14].
- U-Net architecture: a specialized deep learning model designed for biomedical image segmentation, known for its high performance and efficiency [15].
- Active contour models: used to delineate object boundaries in images by evolving a curve based on image gradients [16].
- Random forests: an ensemble learning method that can be used for image segmentation by classifying pixels based on a set of decision trees [17,18].

Software and Packages for Automated Tools in Thoracic Aortic Surgery

Advancements in neural networks have enabled the development of software platforms that integrate complex algorithms for precise analysis of aortic CT images. These tools bridge computational methods and clinical applications, enhancing surgical planning and patient outcomes. This section highlights key software solutions, emphasizing their utility and impact in cardiac surgery.

Mimics Medical v19.0 served as a foundational algorithm, validated in studies for segmenting aortic anatomy and evaluating preoperative metrics [9,22]. Building on this foundation, Mimics Medical v22.0 introduced significant advancements tailored to Thoracic Endovascular Aortic Repair (TEVAR) [23,24]. The newer version features automated segmentation and precise measurements of key anatomical structures, such as the aortic arch and pulmonary artery, making the newer version better equipped to handle complex pathologies. These updates underscore the evolution of the software toward greater precision and clinical utility in planning endovascular interventions. The ability to plan TEVAR procedures preoperatively allows for more accurate stent sizing and better long-term outcomes for patients with thoracic aortic pathologies. However, limitations remain, including challenges in reconstructing thin structures, such as the intimal flap in aortic dissections, and a reliance on high-quality imaging data for accurate segmentation and three-dimensional (3D) reconstruction.

In addition, 3mensio is a commercially available software widely used in vascular and structural heart interventions, including TAVR, EVAR, and left atrial appendage closure (LAAC). The software utilizes CNNs to automate critical measurements, including aortic diameters, annular sizing, and stent landing zones, while generating detailed 3D reconstructions from CTA scans. However, the proprietary algorithms in 3mensio lack transparency regarding training data, and the performance of the software is heavily reliant on high-quality imaging, which can be affected by acquisition variability. Limited customization for atypical anatomies, potential integration challenges with existing systems, and significant licensing costs also present barriers to its broader application. Despite these limitations, 3mensio remains one of the most widely adopted tools in clinical practice, offering streamlined workflows and improved outcomes for endovascular procedures [21–23].

Table 1. Summary of different automation techniques and tools for segmentation and feature extraction.

Technique/tool	Description	Advantages	Applications	References
Convolutional neural network	Deep learning models that utilize convolutional layers to learn and extract features from images by leveraging local receptive fields to capture spatial hierarchies and automatically learn features from varied scales and orientations	- High accuracy in detecting complex features - Ability to generalize well to unseen data with augmentation - Robust against noise and variability in medical images - Handles multiple imaging modalities of input data (e.g., CT, MRI)	- Aorta segmentation for diameter measurement - Pathology detection (e.g., atherosclerotic plaque or aneurysms) - Disease risk prediction (e.g., major adverse cardiac events (MACEs)).	Taye, 2023 [11], Jha *et al*., 2020 [12], Shin *et al*., 2016 [13], and Gu *et al*., 2021 [14]
U-Net architecture	A specialized CNN architecture designed for biomedical image segmentation, featuring a contracting path and an expansive path and distinguished by its encoder-decoder architecture with skip connections	- Excellent performance even with small datasets - Captures fine details using skip connections - Provides high-resolution spatial information critical for organ-level segmentation.	- Accurate aortic wall segmentation for calcification scoring - Established heart and lung CT models	Ronneberger *et al*., 2015 [15] and Zhou *et al*., 2018 [19]
Active contour models	Algorithms that evolve a curve to delineate object boundaries based on image gradients using internal and external forces	- Accurate delineation of boundaries in noisy images - Handles irregular and complex shapes effectively - Minimal training data required - Works with both static and dynamic images	- Ideal for tubular structure segmentation, such as blood vessels or bronchi - Accurate wall delineation for stent placement planning	Natalia *et al*., 2020 [16] and Young *et al*., 2019 [20]
Random forests	Ensemble learning method that uses multiple decision trees for classification and regression. Utilizes bootstrapping and feature randomness to robustly classify pixels, avoiding overfitting in high-dimensional, limited datasets	- Robust against overfitting with high-dimensional datasets - Performs well on small datasets - Can handle multimodal data (e.g., images with clinical metadata).	- Classifying calcification regions - Predicting plaque vulnerability in cardiovascular imaging - Early detection of abnormalities in small datasets	Polan *et al*., 2016 [18] and Yang *et al*., 2020 [17]
Thresholding	Basic image processing technique that segments images by applying global or adaptive intensity thresholds	- Computationally efficient - Simple to implement for binary segmentation - Useful for preprocessing before advanced techniques are applied.	- Detecting high-density calcifications in CT scans - Quickly isolates regions of interest (ROI) for downstream segmentation analysis	Houssein *et al*., 2021 [21] and Lareyre *et al*., 2019 [22]

Table 1. Continued.

Technique/tool	Description	Advantages	Applications	References
Region growing	Method that segments regions by iteratively including neighboring pixels with similar properties of connectivity and intensity similarity	- Handles homogeneous regions well - Adaptive to different intensities for segmentation - Intuitive and computationally efficient for localized regions	- Segmentation of homogenous aortic regions, such as clear boundaries in calcified or soft plaque - Identifying aneurysmal segments	Raja *et al*., 2024 [23]
3D reconstruction techniques	Advanced imaging methods that integrate 2D slices into detailed 3D models	- Enables visualization of complex anatomical relationships - Useful for preoperative planning and intervention - Supports volumetric analysis	- Creating 3D aortic models for surgical planning - Quantifying aortic arch curvature and tortuosity - Identifying multi-planar abnormalities	Ghosh *et al*., 2022 [24]
Edge detection	Techniques that identify edges within images, often using gradient-based methods.	- Highlights boundaries effectively - Useful for feature extraction in noisy environments - Computationally efficient for preprocessing	- Identifying aortic borders for manual or automated segmentation - Extracting vessel outlines for luminal diameter calculation and stent positioning	Harouni *et al*., 2021 [25]
Deep learning ensembles	Combination of multiple deep learning models to improve segmentation accuracy and robustness.	- Improves performance through model diversity - Reduces bias and variance - Allows integration of multiple architectures to exploit their unique strengths	- Integrating anatomical segmentation with calcification scoring - Cross-sectional imaging to volumetric segmentation - Accurate segmentation of multi-organ structures simultaneously	Ganaie *et al*., 2022 [26]

Abbreviations: CT, computed tomography; CNN, convolutional neural network; ECG, electrocardiogram; ROI, region of interest; MACEs, major adverse cardiac events; MRI, magnetic resonance imaging; 2D, two-dimensional; 3D, three-dimensional.

Table 2. Evaluation of automated tools for thoracic artery surgery research.

Software/package name	Algorithm	Data input/output	Clinical application	Validation studies	Limitation of studies	References
Mimics Medical v.22.0	CNNs	Three-dimensional CT images of the thoracic aorta and pulmonary arteries/automated segmentations of the thoracic aorta and measurements of aortic arch metrics	Planning of TEVAR	Validated with 70 CT scans	CNN training was performed on images of healthy subjects and was only tested on a few pathological cases	Saitta *et al*., 2022 [27], Kan *et al*., 2021 [28]
3mensio	CNNs	CTA images/automated measurements and 3D reconstructions of thoracic aorta	Planning of TAVR, TAVI, EVAR, and LAAC	Validated in various external studies (with 90 to 3318 patients)	Performance is heavily reliant on high-quality imaging and there is limited customization for atypical anatomies	de Vaan *et al*., 2012 [29], Benedetti *et al*., 2011 [30], Álvarez-Covarrubias *et al*., 2024 [31]
PRAEVAorta	U-Net and CNNs	Post-EVAR CT scans/volumetric and surface measurements of the aneurysm sac and neck	Post-EVAR surveillance	Validated with 48 early post-EVAR CT scans and 101 follow-up CT scans. Version 2 was validated with 49 patients (98 CTA images)	Analysis was limited to infrarenal AAAs. Further validation is needed for complex aneurysms, including pararenal and visceral segments	Caradu *et al*., 2022 [3]; van Tongeren *et al*., 2025 [2]; Alkhatib *et al*., 2024 [38]
ITK-snap, 3D Slicer	CNN and 3D U-Net architecture	Three-dimensional CT images of the thoracic aorta and pulmonary arteries/automated segmentations of the thoracic aorta and measurements of aortic arch metrics	Planning of TEVAR and double aortic arch evaluation	Validated with 70 CT scans	The CNN training was performed on images of healthy subjects	Saitta *et al*., 2022 [27] and Avnioglu *et al*., 2022 [32]
Endoleak Augmentor	CNNs	CTA images/segmentation maps indicating the presence of endoleak	Endoleak detection post-EVAR	Validated using 1940 CTA slices, of which 746 were positive for endoleaks	Data came from a single medical center, sample sizes including the test subset were small	Talebi *et al*., 2020 [33] and Nowak *et al*., 2024 [34]
TeraRecon	Proprietary deep learning-based algorithms	CT angiography scans of the abdominal aorta and endograft	Evaluation and follow-up of endograft position post-EVAR	Validated in multiple studies involving 5 to 65 patients, mostly for endoleaks	Primarily visualization-based; lacks fully automated segmentation and quantitative force analysis	Figueroa *et al*., 2010 [37] Lee, 2007 [39], and Yoon & Mell, 2020 [40]
Endosize	Boundary-based segmentation	Spiral CT angiography images	Preoperative sizing EVAR	Validated internally with 32 scans for EVAR patient	Retrospective study design prevented same observer variability comparison	Kaladji *et al*., 2010 [41]
Syngo.via post-processing software (v. VB60A_HF04)	Deep learning-based algorithms	Chest CT scans/automated detection and volume measurement of thoracic aortic calcifications	Improved the accuracy of detecting thoracic aortic calcifications	Validated with 100 chest CT scans from 91 patients	Limited sample size and retrospective study design	Saffar *et al*., 2024 [35] and Rayner *et al*., 2024 [36]
AI-Rad Companion Chest CT VA20	Deep learning-based algorithms	CT images/automated detection and volume measurement of thoracic aortic calcifications	Improving the accuracy of detecting thoracic aortic calcifications	Validated using thoracic CT images of 237 patients and pelvic CT images of 102 patients	Some cases still required manual correction	Marschner *et al*., 2022 [42]

Abbreviations: AAA, abdominal aortic aneurysm; CTA, computed tomography angiography; EVAR, endovascular aneurysm repair; LAAC, left atrial appendage closure; TAVI, transcatheter aortic valve implantation; TEVAR, thoracic endovascular aortic repair.

Open-source tools, such as ITK-Snap and 3D Slicer, are accessible for download and can be operated on personal computers. ITK-Snap focuses on manual and semi-automated segmentation, incorporating ML-assisted workflows to streamline the segmentation of aneurysms and aortic dissections [32]. Moreover, the intuitive interface and real-time feedback of ITK-Snap make this software suitable for smaller centers or cases requiring detailed clinician oversight [27,53]. The 3D Slicer software can combine a modular design with advanced algorithms, such as Mask R-CNN, enabling a range of clinical tasks from image registration to quantitative assessment [54]. For example, the Aortic Annulus Analysis module in 3D Slicer can be used in transcatheter aortic valve replacement (TAVR) planning, offering precise measurements that inform device selection and reduce procedural risks. However, a limitation of these open-source tools is their current lack of integration with hospital picture archiving and communication systems (PACS), which restricts their use with patient-specific data; thus, these tools are primarily utilized with anonymized datasets in a research capacity [27].

Endoleak Augmentor is a deep learning-based tool utilizing CNNs to detect endoleaks in post-EVAR patients by analyzing CTA images and segmentation maps, enhancing diagnostic accuracy [33]. However, the development of Endoleak Augmentor was based on a small dataset from a single institution (20 CTAs, 10 with endoleaks), which limits its generalizability [34]. Syngo.via post-processing software (v. VB60A_HF04) and AI-Rad Companion Chest CT VA20 employ deep learning algorithms for automated detection and volumetric assessment of thoracic aortic calcifications from chest CT scans. These tools support improved risk stratification and patient management [35,36]. Despite their clinical utility, both platforms and TeraRecon, another widely used proprietary system for 3D aortic visualization, are limited by their closed-source algorithms [37]. This lack of transparency hinders user insight into model decisions and restricts customization or integration with research-grade analytical tools. Moreover, their performance can be highly sensitive to image quality, scan protocols, and contrast timing, which may affect reproducibility across different clinical settings.

By incorporating these tools, surgeons and radiologists can gain access to intuitive, clinically relevant solutions that maximize the diagnostic and predictive potential of advanced neural networks [3,26]. While the studies acknowledge the limitations and the need for further validation, we aim to emphasize their versatility. Despite the complexity of their underlying algorithms, these platforms effectively translate advanced computations into practical, actionable insights for thoracic aortic surgery, streamlining workflows, and enhancing patient evaluation.

Real-World Applications of AI in Aortic Imaging and Surgical Planning

An ideal new software tool should provide increased workflow efficiency and enhanced clinical decision-making value, while also integrating easily with current electronic health systems and being relatively simple to use. The tools utilized in the following studies demonstrate significant potential for aiding in surgical planning and emphasize the predictive value of incorporating radiological features, often imperceptible to human detection, in assessing patient outcomes. Below, we explore notable studies that illustrate the application of new, exploratory technologies in real-world clinical cohorts and patient care, with key papers summarized in Table 3.

Segmentation and dimensional analysis of the aorta are fundamental to surgical planning, particularly for procedures such as TEVAR and EVAR. Koo *et al.* [43] developed a CNN-based segmentation tool to establish normative aortic size ranges across zones 0–8, utilizing a cohort of 704 healthy Korean adults. Their findings revealed that the aortic size was significantly larger in males and increased with age by approximately 1 millimeter (mm) per decade, providing baseline values for identifying abnormal growth. The segmentation masks of the tool demonstrated excellent agreement with manual corrections, offering surgeons reliable measurements for procedural planning. However, the exclusion of older patients in the study and the reliance on non-gated CT scans, which may introduce cardiac motion artifacts, particularly in the ascending aorta, highlight areas for future refinement [43]. Similarly, Krebs *et al.* [44] applied an automated deep learning model to evaluate aortic growth in patients with acute, uncomplicated type B aortic dissection (auTBAD). Their study revealed rapid growth in over half the patients, suggesting a potential role for automated tools in flagging high-risk cases for closer evaluation. While promising, the small sample size (59 patients) underscores the need for larger studies to validate these findings and refine predictive thresholds for intervention [44].

Radiomics, a technique for extracting quantitative features from medical images, has shown significant promise in thoracic aortic surgery. Zhou *et al.* [45] applied radiomics to non-contrast CT scans to diagnose acute aortic dissection (AAD), focusing on intensity, texture, and shape features. Key attributes, such as histogram-based intensity metrics and gray-level co-occurrence matrix textures, enabled high diagnostic accuracy, providing a non-invasive alternative for patients contraindicated for contrast agents [45]. This approach enhances diagnostic workflows and facilitates timely intervention in emergent settings. Expanding on this, Lu *et al.* [46] developed a radiomics-based model to predict adverse events (AEs) following TEVAR in patients with uncomplicated type B aortic dissections. By

Table 3. Summary of recent studies on clinically correlated radiomic features in aortic CT analysis.

Study Title	Objective	Methodology	Key Radiological Features	Key Findings	Limitations	References
The diagnostic value of a non-contrast computed tomography scan-based radiomics model for acute aortic dissection	To investigate the diagnostic value of a CT scan-based radiomics model for AAD	Retrospectively selected patients clinically diagnosed with AAD. CT images were acquired, imported into 3D Slicer, and processed by radiologists. Radiomic features extracted on PyRadiomics platform.	1203 characteristic parameters: first-order statistics, geometric descriptive features, and texture features, such as gray-level co-occurrence, size-zone, run-length, and difference matrices	The non-contrast CT scan-based radiomics model accurately facilitated AAD diagnosis	Only 50 patients included in each group, retrospective, and only the largest lesion layer was selected for depicting the ROI	Zhou *et al.*, 2021 [45]
Deep Learning Based Automatic Segmentation of the Thoracic Aorta from Chest Computed Tomography in Healthy Korean Adults	To establish reference values for aortic size using a fully automated deep learning based segmentation method	Retrospective study using 704 healthy adults with chest CT scans. A CNN was trained on 3D CT images for automatic aorta segmentation based on vascular surgery classifications. Masks reviewed by radiologists.	Aortic size in zones 0–8	Aortic size was significantly larger in males; increases with age by $\sim$1 mm per decade; segmentation masks comparable to manually corrected ones	Chest CT without ECG gated scan could introduce cardiac motion artifacts especially at ascending aorta. Study cohort was relatively young, with an average age of 50.6 $\pm$ 7.5 years, and limited to Korean.	Koo *et al.*, 2025 [43]
Volumetric analysis of acute uncomplicated type B aortic dissection using an automated deep learning aortic zone segmentation model	To develop an automatic ML model for aortic zone segmentation to compare aortic growth in patients with auTBAD	Retrospective study with 59 patients having serial CT scans. An ML model was trained using four-fold cross-validation, with images annotated based on Society for Vascular Surgery and Society of Thoracic Surgeons criteria.	Aortic zone volumes, rate of aortic growth	Rapid growth observed in 56% of patients; no baseline differences between groups; performance of model was best in zones 5 and 9 (Dice coefficient of 0.91 in zone 9)	Small sample size, limited generalizability; no differences in baseline zone volumes between growth groups	Krebs *et al.*, 2024 [44]
Deep learning-based radiomics of computed tomography angiography to predict adverse events after initial endovascular repair for acute uncomplicated Stanford type B aortic dissection	To develop a predictive model integrating deep learning-derived radiomic features from CTA and clinical biomarkers to forecast AEs in auTBAD patients undergoing TEVAR	Retrospective study with 369 patients who underwent TEVAR for auTBAD. Deep learning CNN extracted features from CTA. Feature selection using ANOVA and LASSO, followed by modeling with XGBoost.	Rad-Score, CTA-derived radiomic features, clinical biomarkers (albumin, CRP)	Model exhibited an AUC of 1.000 (training cohort) and 0.990 (internal validation), with excellent accuracy, precision, and sensitivity in predicting postoperative AEs	The nature of the study was retrospective, and individual surgical variances could have influenced outcomes	Lu *et al.*, 2024 [46]
Using machine learning to predict outcomes of patients with blunt traumatic aortic injuries	To develop an ML model to predict mortality risk factors in patients with BTAI	Retrospective analysis of 702 patients with BTAI from the Aortic Trauma Foundation registry. Machine learning model (STREAMLINE) compared with logistic regression and AUC analysis.	Injury location, age, aortic injury grade	STREAMLINE model and LR model both had high AUCs (0.869 and 0.840, respectively) for predicting in-hospital mortality. Variables differed between models	Limited to a single cohort; model performance needs validation in other cohorts	Lu *et al.*, 2024 [47]
A fully automated artificial intelligence-driven software for planning of transcatheter aortic valve replacement	To develop and validate an AI-powered software to automatically extract anatomical measurements for TAVR planning.	Retrospective analysis comparing AI-generated measurements from 100 CT scans with expert manual measurements using commercially available software packages.	Annular measurements, ascending aorta dimensions	AI-generated measurements showed excellent agreement with expert measurements (correlation $>$0.95) and low mean differences ($\leq$1.4 mm). High agreement with implant sizing (87–88%)	Limited to a sample of 100 CT scans; further validation needed across different institutions and patient populations	Toggweiler *et al.*, 2024 [48]
A Deep Learning-Based and Fully Automated Pipeline for Thoracic Aorta Geometric Analysis and Planning for Endovascular Repair from Computed Tomography	To develop a fully automated CNN pipeline to segment the thoracic aorta and quantify geometric features relevant for TEVAR planning	Trained a CNN using 395 CT scans for segmentation, validated on 70 scans. The CNN was embedded in a computational pipeline to extract aortic metrics like maximum diameters, angulation, and tortuosity.	Aortic arch centerline radius, maximum diameters, angulation, tortuosity	The CNN achieved a Dice score of 0.95 and was able to accurately segment 9 pathological cases. Significant differences in parameters between standard and common origin of the innominate and left carotid artery arches were found	CNN training, which requires a large number of CT scans, was performed on images of healthy subjects	Saitta *et al.*, 2022 [27]

Abbreviations: AAD, acute aortic dissection; AE, adverse event; ECG, electrocardiogram; ML, machine learning; TBAD, Type B aortic dissection; AUC, area under the curve; BTAI, blunt thoracic aortic injury.

integrating CTA-derived features with clinical biomarkers such as C-reactive protein (CRP) and albumin, the model demonstrated exceptional predictive performance with an external validation area under the curve (AUC) of 0.985 [46]. This tool enables surgeons to stratify patients by risk, allowing for personalized postoperative care and targeted follow-up strategies. For blunt thoracic aortic injury (BTAI), Lu *et al*. [46] created the STREAMLINE ML model to predict mortality risk. Indeed, the STREAMLINE ML model incorporated factors such as injury location, age, and grade, streamlining trauma care by identifying patients most in need of urgent intervention [47]. These advancements in radiomics and ML demonstrate their potential to refine diagnostic accuracy, predict complications, and personalize management strategies in thoracic aortic surgery.

AI-powered tools are also proving transformative in procedural planning. Toggweiler *et al*. [48] validated an in-house developed software that automates anatomical measurements for TAVR planning. The tool demonstrated strong agreement with expert manual measurements, with correlations exceeding 0.95 and high concordance in prosthetic sizing decisions. Thus, by eliminating the variability and time burden of manual measurements, this software allows surgeons to focus on optimizing procedural outcomes while reducing reliance on human radiologists [48]. For TEVAR planning, Saitta *et al*. [27] developed a fully automated, CNN-based pipeline to extract key geometric features, including centerline radius, angulation, and tortuosity. Their model achieved high ground-truth similarity scores and accurately quantified proximal landing zone parameters, which are critical for stent graft selection. By offering detailed geometric insights, this tool enables surgeons to refine patient-specific procedural strategies, minimizing the risk of complications [27].

Advanced imaging tools are transforming thoracic aortic surgery by enhancing diagnostic workflows, improving surgical planning precision, and providing data-driven insights into patient outcomes. By integrating features beyond traditional size metrics, such as wall stress and calcification patterns, these tools enable clinicians to make more nuanced, patient-specific decisions, ensuring timely and tailored interventions.

Future Directions and Challenges

Advanced imaging technologies, including radiomics, deep learning, and hybrid CT modalities, have the potential to transform thoracic aortic surgery by improving diagnostic accuracy, surgical planning, and personalized risk assessment. However, widespread adoption faces significant hurdles, such as limited dataset diversity, the absence of standardized validation protocols, and challenges in integrating these tools into hospital PACS systems. While many of these technologies are open-source and lightweight, ensuring secure and seamless access to patient-specific data remains a major obstacle.

To unlock the full potential of these innovations, it is essential to investigate the effectiveness of software and workflows through conducting multicenter validation studies under real-world conditions. Seamlessly integrating advanced imaging tools into clinical workflows would enhance collaboration among radiologists, cardiologists, and cardiovascular surgeons, more easily fostering a multidisciplinary approach to care. By highlighting the utility of these technologies, this paper emphasizes the importance of incorporating these models into routine practice to enable precise, data-driven, and patient-centered care in thoracic aortic surgery.

Conclusion

Artificial intelligence driven tools are rapidly transforming computed tomography analysis in thoracic aortic surgery, offering significant advances in segmentation accuracy, radiomic feature extraction, and outcome prediction. By automating critical imaging tasks, these technologies can enhance surgical planning, streamline workflows, and support more personalized patient care. However, widespread adoption will depend on standardized validation, improved dataset diversity, and seamless integration into clinical systems. Continued multidisciplinary collaboration and real-world testing are essential to fully realize the clinical potential of AI in thoracic aortic imaging.

Author Contributions

DC and BLS designed the research study. DC, SS, and BLS performed the research and analyzed the data. All authors contributed to writing and editorial changes in the manuscript. Final guidance was provided by BLS. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

Not applicable.

Acknowledgment

Not applicable.

Funding

This research received no external funding.

Conflict of Interest

The authors declare no conflict of interest.

References

[1] Carroll BJ, Schermerhorn ML, Manning WJ. Imaging for acute aortic syndromes. Heart (British Cardiac Society). 2020; 106: 182–189. https://doi.org/10.1136/heartjnl-2019-314897.

[2] van Tongeren OLRM, Vanmaele A, Rastogi V, Hoeks SE, Verhagen HJM, de Bruin JL. Volume Measurements for Surveillance after Endovascular Aneurysm Repair using Artificial Intelligence. European Journal of Vascular and Endovascular Surgery: the Official Journal of the European Society for Vascular Surgery. 2025; 69: 61–70. https://doi.org/10.1016/j.ejvs.2024.08.045.

[3] Caradu C, Pouncey AL, Lakhlifi E, Brunet C, Bérard X, Ducasse E. Fully automatic volume segmentation using deep learning approaches to assess aneurysmal sac evolution after infrarenal endovascular aortic repair. Journal of Vascular Surgery. 2022; 76: 620–630.e3. https://doi.org/10.1016/j.jvs.2022.03.891.

[4] Murillo H, Molvin L, Chin AS, Fleischmann D. Aortic Dissection and Other Acute Aortic Syndromes: Diagnostic Imaging Findings from Acute to Chronic Longitudinal Progression. Radiographics: a Review Publication of the Radiological Society of North America, Inc. 2021; 41: 425–446. https://doi.org/10.1148/rg.2021200138.

[5] Isselbacher EM, Preventza O, Hamilton Black J, 3rd, Augoustides JG, Beck AW, Bolen MA, *et al*. 2022 ACC/AHA Guideline for the Diagnosis and Management of Aortic Disease: A Report of the American Heart Association/American College of Cardiology Joint Committee on Clinical Practice Guidelines. Circulation. 2022; 146: e334–e482. https://doi.org/10.1161/CIR.0000000000001106.

[6] Arnett DK, Blumenthal RS, Albert MA, Buroker AB, Goldberger ZD, Hahn EJ, *et al*. 2019 ACC/AHA Guideline on the Primary Prevention of Cardiovascular Disease: A Report of the American College of Cardiology/American Heart Association Task Force on Clinical Practice Guidelines. Circulation. 2019; 140: e596–e646. https://doi.org/10.1161/CIR.0000000000000678.

[7] Visseren FLJ, Mach F, Smulders YM, Carballo D, Koskinas KC, Bäck M, *et al*. 2021 ESC Guidelines on cardiovascular disease prevention in clinical practice: Developed by the Task Force for cardiovascular disease prevention in clinical practice with representatives of the European Society of Cardiology and 12 medical societies With the special contribution of the European Association of Preventive Cardiology (EAPC). European Heart Journal. 2021; 42: 3227–3337. https://doi.org/10.1093/eurheartj/ehab484.

[8] Graffy PM, Liu J, O'Connor S, Summers RM, Pickhardt PJ. Automated segmentation and quantification of aortic calcification at abdominal CT: application of a deep learning-based algorithm to a longitudinal screening cohort. Abdominal Radiology (New York). 2019; 44: 2921–2928. https://doi.org/10.1007/s00261-019-02014-2.

[9] Chen D, Zhang X, Mei Y, Liao F, Xu H, Li Z, *et al*. Multi-stage learning for segmentation of aortic dissections using a prior aortic anatomy simplification. Medical Image Analysis. 2021; 69: 101931. https://doi.org/10.1016/j.media.2020.101931.

[10] Bonechi S, Andreini P, Mecocci A, Giannelli N, Scarselli F, Neri E, *et al*. Segmentation of aorta 3D CT images based on 2D convolutional neural networks. Electronics (Switzerland). 2021; 10: 2559. https://doi.org/10.3390/electronics10202559.

[11] Taye MM. Theoretical understanding of convolutional neural network: Concepts, architectures, applications, future directions. Computation. 2023; 11: 52. https://doi.org/10.3390/computation11030052.

[12] Jha D, Riegler MA, Johansen D, Halvorsen P, Johansen HD. Doubleu-net: A deep convolutional neural network for medical image segmentation. In 2020 IEEE 33rd International symposium on computer-based medical systems (CBMS) (pp. 558–564). IEEE. 2020.

[13] Shin HC, Roth HR, Gao M, Lu L, Xu Z, Nogues I, *et al*. Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning. IEEE Transactions on Medical Imaging. 2016; 35: 1285–1298. https://doi.org/10.1109/TMI.2016.2528162.

[14] Gu R, Wang G, Song T, Huang R, Aertsen M, Deprest J, *et al*. CA-Net: Comprehensive Attention Convolutional Neural Networks for Explainable Medical Image Segmentation. IEEE Transactions on Medical Imaging. 2021; 40: 699–711. https://doi.org/10.1109/TMI.2020.3035253.

[15] Ronneberger O, Fischer P, Brox T. U-Net: Convolutional Networks for Biomedical Image Segmentation. In Navab N, Hornegger J, Wells WM, Frangi AF (eds.) Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015 (pp. 234–241). Springer International Publishing: Cham. 2015.

[16] Natalia F, Meidia H, Afriliana N, Young JC, Sudirman S. Contour evolution method for precise boundary delineation of medical images. TELKOMNIKA: Telecommunication, Computing, Electronics and Control. 2020; 18: 1621–1632.

[17] Yang C, Ojha BD, Aranoff ND, Green P, Tavassolian N. Classification of aortic stenosis using conventional machine learning and deep learning methods based on multi-dimensional cardio-mechanical signals. Scientific Reports. 2020; 10: 17521. https://doi.org/10.1038/s41598-020-74519-6.

[18] Polan DF, Brady SL, Kaufman RA. Tissue segmentation of computed tomography images using a Random Forest algorithm: a feasibility study. Physics in Medicine and Biology. 2016; 61: 6553–6569. https://doi.org/10.1088/0031-9155/61/17/6553.

[19] Zhou Z, Siddiquee MMR, Tajbakhsh N, Liang J. UNet++: A Nested U-Net Architecture for Medical Image Segmentation. Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support: 4th International Workshop, DLMIA 2018, and 8th International Workshop, ML-CDS 2018, Held in Conjunction with MICCAI 2018. Granada, Spain. 2018; 11045: 3–11. https://doi.org/10.1007/978-3-030-00889-5_1.

[20] Young JC, Afriliana N, Natalia F, Meidia H, Sudirman S. A study on the suitability of applying active contour evolution models in segmenting and delineating boundaries in medical images. In 2019 5th International Conference on New Media Studies (CONMEDIA) (pp. 232–237). IEEE. 2019.

[21] Houssein EH, Helmy E, Oliva D, Elngar AA, Shaban H. Multi-level thresholding image segmentation based on nature-inspired optimization algorithms: a comprehensive review. In Oliva D, Houssein EH, Hinojosa S (eds.) Metaheuristics in Machine learning: theory and applications (pp. 239–265). Springer: Cham. 2021. https://doi.org/10.1007/978-3-030-70542-8_11.

[22] Lareyre F, Adam C, Carrier M, Dommerc C, Mialhe C, Raffort J. A fully automated pipeline for mining abdominal aortic aneurysm using image segmentation. Scientific Reports. 2019; 9: 13750. https://doi.org/10.1038/s41598-019-50251-8.

[23] Raja NSM, Fernandes SL, Dey N, Satapathy SC, Rajinikanth V. Contrast enhanced medical MRI evaluation using Tsallis entropy and region growing segmentation. Journal of Ambient Intelligence and Humanized Computing. 2024; 15, 961–972. https://doi.org/10.1007/s12652-018-0854-8.
[24] Ghosh RM, Jolley MA, Mascio CE, Chen JM, Fuller S, Rome JJ, *et al*. Clinical 3D modeling to guide pediatric cardiothoracic surgery and intervention using 3D printed anatomic models, computer aided design and virtual reality. 3D Printing in Medicine. 2022; 8: 11. https://doi.org/10.1186/s41205-022-00137-9.
[25] Harouni M, Karimi M, Rafieipour S. Precise segmentation techniques in various medical images. Artificial Intelligence and Internet of Things (pp. 117–166). CRC Press: Boca Raton, FL. 2021.
[26] Ganaie MA, Hu M, Malik AK, Tanveer M, Suganthan PN. Ensemble deep learning: A review. Engineering Applications of Artificial Intelligence. 2022; 115: 105151.
[27] Saitta S, Sturla F, Caimi A, Riva A, Palumbo MC, Nano G, *et al*. A Deep Learning-Based and Fully Automated Pipeline for Thoracic Aorta Geometric Analysis and Planning for Endovascular Repair from Computed Tomography. Journal of Digital Imaging. 2022; 35: 226–239. https://doi.org/10.1007/s10278-021-00535-1.
[28] Kan X, Ma T, Lin J, Wang L, Dong Z, Xu XY. Patient-specific simulation of stent-graft deployment in type B aortic dissection: model development and validation. Biomechanics and Modeling in Mechanobiology. 2021; 20: 2247–2258. https://doi.org/10.1007/s10237-021-01504-x.
[29] de Vaan J, Verstraeten L, de Jaegere P, Schultz C. The 3mensio Valves™ multimodality workstation. EuroIntervention: Journal of EuroPCR in Collaboration with the Working Group on Interventional Cardiology of the European Society of Cardiology. 2012; 7: 1464–1469. https://doi.org/10.4244/EIJV7I12A228.
[30] Benedetti G, Schlueter M, Giannini C, Coceani M, Delle Donne M, Guarracino F, *et al*. 3-mensio software for the measurement of the aortic annulus before TAVI: agreement with multi-slice tomography and with echocardiography. European Heart Journal. 2011; 32: 892–892.
[31] Álvarez-Covarrubias HA, Altaner N, Adolf R, Jurisic M, Horban E, Pellegrini C, *et al*. Aortic valve calcification volume and prognosis in patients undergoing transcatheter aortic valve implantation. Revista Espanola De Cardiologia (English Ed.). 2024; S1885–S1885–5857(24)00310–4. https://doi.org/10.1016/j.rec.2024.10.005.
[32] Avnioglu S, Dikici R, Etli M. 3D modeling and comparative analysis of the double arcus aorta case. The International Journal of Cardiovascular Imaging. 2022; 38: 2263–2268. https://doi.org/10.1007/s10554-022-02675-z.
[33] Talebi S, Madani MH, Madani A, Chien A, Shen J, Mastrodicasa D, *et al*. Machine learning for endoleak detection after endovascular aortic repair. Scientific Reports. 2020; 10: 18343. https://doi.org/10.1038/s41598-020-74936-7.
[34] Nowak E, Białecki M, Białecka A, Kazimierczak N, Kloska A. Assessing the diagnostic accuracy of artificial intelligence in post-endovascular aneurysm repair endoleak detection using dual-energy computed tomography angiography. Polish Journal of Radiology. 2024; 89: e420–e427. https://doi.org/10.5114/pjr/192115.
[35] Saffar R, Sperl JI, Berger T, Vojtekova J, Kreibich M, Hagar MT, *et al*. Accuracy of a deep learning-based algorithm for the detection of thoracic aortic calcifications in chest computed tomography and cardiovascular surgery planning. European Journal of Cardio-thoracic Surgery: Official Journal of the European Association for Cardio-thoracic Surgery. 2024; 65: ezae219. https://doi.org/10.1093/ejcts/ezae219.
[36] Rayner C, Eaves S, Paleri S, Hayat U, Adams H. Head to head comparison of software programmes for preprocedural MDCT assessment and outcomes in Tavi. In 72nd Annual Scientific Meeting of the Cardiac Society of Australia and New Zealand. Heart Lung and Circulation. 2024.
[37] Figueroa CA, Taylor CA, Yeh V, Chiou AJ, Gorrepati ML, Zarins CK. Preliminary 3D computational analysis of the relationship between aortic displacement force and direction of endograft movement. Journal of Vascular Surgery. 2010; 51: 1488–1497; discussion 1497. https://doi.org/10.1016/j.jvs.2010.01.058.
[38] Alkhatib F, Jamshidian M, Liepvre DL, Bernard F, Minvielle L, Fondanèche A, *et al*. Towards Full Automation of Geometry Extraction for Biomechanical Analysis of Abdominal Aortic Aneurysm; Neural Network-Based versus Classical Methodologies. arXiv. 2024. (preprint)
[39] Lee WA. Endovascular abdominal aortic aneurysm sizing and case planning using the TeraRecon Aquarius workstation. Vascular and Endovascular Surgery. 2007; 41: 61–67. https://doi.org/10.1177/1538574406296244.
[40] Yoon WJ, Mell MW. Outcome comparison of thoracic endovascular aortic repair performed outside versus inside proximal landing zone length recommendation. Journal of Vascular Surgery. 2020; 72: 1883–1890. https://doi.org/10.1016/j.jvs.2020.03.033.
[41] Kaladji A, Lucas A, Kervio G, Haigron P, Cardon A. Sizing for endovascular aneurysm repair: clinical evaluation of a new automated three-dimensional software. Annals of Vascular Surgery. 2010; 24: 912–920. https://doi.org/10.1016/j.avsg.2010.03.018.
[42] Marschner S, Datar M, Gaasch A, Xu Z, Grbic S, Chabin G, *et al*. A deep image-to-image network organ segmentation algorithm for radiation treatment planning: principles and evaluation. Radiation Oncology (London, England). 2022; 17: 129. https://doi.org/10.1186/s13014-022-02102-6.
[43] Koo HJ, Lee JG, Lee JB, Kang JW, Yang DH. Deep Learning Based Automatic Segmentation of the Thoracic Aorta from Chest Computed Tomography in Healthy Korean Adults. European Journal of Vascular and Endovascular Surgery: the Official Journal of the European Society for Vascular Surgery. 2025; 69: 48–58. https://doi.org/10.1016/j.ejvs.2024.07.030.
[44] Krebs JR, Imran M, Fazzone B, Viscardi C, Berwick B, Stinson G, *et al*. Volumetric analysis of acute uncomplicated type B aortic dissection using an automated deep learning aortic zone segmentation model. Journal of Vascular Surgery. 2024; 80: 1025–1034.e4. https://doi.org/10.1016/j.jvs.2024.06.001.
[45] Zhou Z, Yang J, Wang S, Li W, Xie L, Li Y, *et al*. The diagnostic value of a non-contrast computed tomography scan-based radiomics model for acute aortic dissection. Medicine. 2021; 100: e26212. https://doi.org/10.1097/MD.0000000000026212.
[46] Lu X, Gong W, Yang W, Peng Z, Zheng C, Zha Y. Deep learning-based radiomics of computed tomography angiography to predict adverse events after initial endovascular repair for acute uncomplicated Stanford type B aortic dissection. European Journal of Radiology. 2024; 175: 111468. https://doi.org/10.1016/j.ejrad.2024.111468.
[47] Lu E, Dubose J, Venkatesan M, Wang ZP, Starnes BW, Saqib NU, *et al*. Using machine learning to predict outcomes of patients with blunt traumatic aortic injuries. Journal of Trauma and Acute Care Surgery. 2024; 97: 258–265. https://doi.org/10.1097/TA.0000000000004322.
[48] Toggweiler S, Wyler von Ballmoos MC, Moccetti F, Douverny A, Wolfrum M, Imamoglu Z, *et al*. A fully automated artificial intelligence-driven software for planning of transcatheter aortic valve replacement. Cardiovascular Revascularization Medicine: Including Molecular Interventions. 2024; 65: 25–31. https://doi.org/10.1016/j.carrev.2024.03.008.

[49] Janiesch C, Zschech P, Heinrich K. Machine learning and deep learning. Electronic Markets. 2021; 31: 685–695.

[50] Ko JP, Goldstein JM, Latson LA, Jr, Azour L, Gozansky EK, Moore W, *et al*. Chest CT Angiography for Acute Aortic Pathologic Conditions: Pearls and Pitfalls. Radiographics: a Review Publication of the Radiological Society of North America, Inc. 2021; 41: 399–424. https://doi.org/10.1148/rg.2021200055.

[51] Varghese C, Harrison EM, O'Grady G, Topol EJ. Artificial intelligence in surgery. Nature Medicine. 2024; 30: 1257–1268. https://doi.org/10.1038/s41591-024-02970-3.

[52] Fernandes SL, Tanik UJ, Rajinikanth V, Karthik KA. A reliable framework for accurate brain image examination and treatment planning based on early diagnosis support for clinicians. Neural Computing and Applications. 2020; 32: 15897–15908. https://doi.org/10.1007/s00521-019-04369-5.

[53] Pradeep K, Sriram S, Vijay J, Priyanka S. Certain investigations on prediction of dissected aorta using computational fluid dynamic analysis. In AIP Conference Proceedings. AIP Publishing. 2022.

[54] Pickhardt PJ, Graffy PM, Zea R, Lee SJ, Liu J, Sandfort V, *et al*. Automated CT biomarkers for opportunistic prediction of future cardiovascular events and mortality in an asymptomatic screening population: a retrospective cohort study. The Lancet. Digital Health. 2020; 2: e192–e200. https://doi.org/10.1016/S2589-7500(20)30025-X.