Austin Journal of Radiology

Open Access

Austin Publishing Group

Systematic Review

Systematic Review of Deep Learning Approaches for Automatic Segmentation of Abdominal Aortic Aneurysm and Thrombus on Computed Tomography Angiography Images

Tarek Khrisat, MD[1*]; Jamie Ashe, MD[1]; Xutong Guo[2]

[1]Lincoln Medical Center, USA

[2]St' George's School of Medicine, USA

***Corresponding author:** Tarek Khrisat*

Lincoln Medical Center, USA.

Email: tarekkhrisat@gmail.com

Received: April 24, 2023

Accepted: May 19, 2023

Published: May 26, 2023

Abstract

Abdominal Aortic Aneurysm (AAA) is a potentially life-threatening condition characterized by the enlargement of the abdominal aorta. Computed Tomography Angiography (CTA) is a widely used diagnostic tool for AAA, and accurate segmentation of the aneurysm and thrombus is critical for treatment planning. Deep learning approaches have shown promise in automating the segmentation process. We conducted a systematic review of the literature to evaluate the performance of deep learning methods for automatic segmentation of AAA and thrombus on CTA images. Six studies were identified that met our inclusion criteria. The studies utilized various deep learning architectures and loss functions to segment AAA and thrombus, and reported performance using metrics such as sensitivity, specificity, accuracy, and Dice coefficient. The results indicate that deep learning methods can achieve high accuracy and Dice coefficient values for segmentation of AAA and thrombus on CTA images. However, the performance of the methods varied depending on the specific architecture and loss function used. Further research is needed to determine the most effective deep learning approach for automatic segmentation of AAA and thrombus on CTA images.

Keywords: Deep learning; Abdominal aortic aneurysm; Thrombus; Computed tomography angiography; Segmentation

Introduction

Abdominal Aortic Aneurysm (AAA) is a potentially life-threatening condition characterized by the enlargement of the abdominal aorta. The prevalence of AAA increases with age and is more common in men than women [1]. The risk of rupture of the aneurysm increases as its size increases, with rupture leading to high mortality rates [2]. Computed Tomography Angiography (CTA) is a widely used diagnostic tool for AAA [3]. Accurate segmentation of the aneurysm and thrombus is critical for treatment planning and follow-up evaluation of the aneurysm [4].

Manual segmentation of AAA and thrombus is a time-consuming and labor-intensive task that requires expertise in medical imaging [5]. Deep learning approaches have shown promise in automating the segmentation process. Deep learning is a subfield of machine learning that utilizes neural networks to learn from data and make predictions [6]. Convolutional Neural Networks (CNNs) are a popular deep learning architecture for image segmentation tasks [7].

Objective

The objective of this study was to conduct a systematic review of the literature to evaluate the performance of deep learning methods for automatic segmentation of AAA and thrombus on CTA images.

Methods

A systematic literature search was conducted using PubMed database to identify studies published in English between January 2020 and April 2023 that utilized deep learning approaches for automatic segmentation of AAA and thrombus on CTA images. The search strategy utilized the following keywords: "artificial intelligence," "computerized tomography angiography," "abdominal aortic aneurysm, "thrombus," and "segmentation." Two reviewers independently screened the titles, abstracts, and full texts of the studies for eligibility based on the following inclusion criteria: (1) studies that utilized deep learning approaches for automatic segmentation of AAA and/or thrombus on CTA images, (2) studies that reported performance metrics for the

Khrisat T © All rights reserved

Citation: Khrisat T. Systematic Review of Deep Learning Approaches for Automatic Segmentation of Abdominal Aortic Aneurysm and Thrombus on Computed Tomography Angiography Images. Austin J Radiol. 2023; 10(2): 1215.

deep learning methods, and (3) studies published in English. Studies that utilized deep learning methods for segmentation of other structures in addition to AAA and thrombus were excluded.

Inclusion Criteria

- PubMed data base
- Published between January 2020-April 2023
- English studies only
- Search criteria: ((ARTIFICIAL INTELLIGENCE) AND (computed tomography angiography)) AND (abdominal aortic aneurysms)
- Full text available only

Exclusion Criteria

- Studies that evaluated other than abdominal aortic aneurysms
- Studies that did not involve auto-segmentation
- Studies based on geometric analysis of the aneurysms

Data Extraction

Data were extracted from the studies on the following:

1) Deep learning architecture, including the type of neural network, number of layers, and number of parameters.

2) Image pre-processing techniques, including image normalization, resizing, and cropping.

3) Type of CT scanner and imaging protocol used.

4) Characteristics of the patient population, including age, gender, and clinical diagnosis.

5) Methods used for ground truth labeling and evaluation metrics, including sensitivity, specificity, and accuracy.

6) Performance of the deep learning model in terms of segmentation accuracy, compared to ground truth segmentation performed by expert radiologists.

The extracted data were tabulated and analyzed to identify patterns and trends in the deep learning approaches used in the studies and their respective performance in segmenting abdominal aortic aneurysms and thrombi.

Discussion

Deep Learning to Automatically Segment and Analyze Abdominal Aortic Aneurysm from Computed Tomography Angiography.

The study by Brutti et al. (2021) used a fully automated deep learning approach to segment and analyze abdominal aortic aneurysms from CT angiography scans. The model was trained using a dataset of 1,010 cases and tested on a separate dataset of 100 cases. The study reported a high accuracy rate of 95.9%, sensitivity of 93.6%, and specificity of 96.6%.

Fully Automatic Volume Segmentation of Infrarenal Abdominal Aortic Aneurysm Computed Tomography Images with Deep Learning Approaches Versus Physician Controlled Manual Segmentation.

Caradu et al. (2021) compared fully automatic volume segmentation of infrarenal abdominal aortic aneurysm CT images using deep learning approaches to physician-controlled manual segmentation. The study used a dataset of 60 cases and reported that the fully automatic deep learning approach was able to achieve a similar level of accuracy to the manual segmentation, with an average Dice similarity coefficient of 0.93.

Fully Automatic Segmentation of Abdominal Aortic Thrombus in Pre-operative CTA Images Using Deep Convolutional Neural Networks.

Wang et al. (2021) used a fully automatic deep convolutional neural network approach to segment abdominal aortic thrombus in pre-operative CTA images. The study used a dataset of 80 cases and reported an overall segmentation accuracy of 93.58%.

Automatic Detection and Segmentation of Thrombi in Abdominal Aortic Aneurysms Using a Mask Region-Based Convolutional Neural Network with Optimized Loss Functions.

Hwang et al. (2021) developed a deep learning model to detect and segment thrombi in abdominal aortic aneurysms using a mask region-based convolutional neural network with optimized loss functions. The study used a dataset of 164 cases and reported a high sensitivity of 94.3%, specificity of 99.3%, and accuracy of 97.1%.

3D Automatic Segmentation of Aortic Computed Tomography Angiography Combining Multi-View 2D Convolutional Neural Networks.

Fantazzini et al. (2020) proposed a 3D automatic segmentation method for aortic CT angiography images using multi-view 2D convolutional neural networks. The study used a dataset of 22 cases and reported an overall segmentation accuracy of 96.51%.

From the extracted data, we can infer that deep learning models using various types of neural networks, such as CNN and LSTM, are effective for automatic segmentation and analysis of abdominal aortic aneurysm and thrombus in CT angiography images.

Pre-processing techniques like image normalization, resizing, and cropping are commonly used to improve the quality of input images. Different CT scanner models and imaging protocols were used in the studies, which may affect the accuracy of the segmentation results.

The patient populations in the studies had varying characteristics, such as age, gender, and clinical diagnosis, which did not appear to have a significant impact on the performance of the deep learning models.

Various ground truth labeling and evaluation metrics, such as sensitivity, specificity, accuracy, and Jaccard coefficient, were used to evaluate the performance of the deep learning models.

Overall, the deep learning models demonstrated high segmentation accuracy compared to ground truth segmentation performed by expert radiologists, indicating their potential usefulness in clinical settings for the diagnosis and treatment of abdominal aortic aneurysm and thrombus.

We can see that all studies used deep learning architectures based on convolutional neural networks, with some variation in terms of the specific architecture used (e.g., 2D vs. 3D, presence of attention mechanisms or residual blocks, etc.). The segmentation accuracy, as measured by the Dice coefficient, also var-

Table 1: Comparison of auto segmentation methods.

Study	Segmentation Method	Dice Coeffcient
Wang et al.	3D U-Net	0.903±0.035
Li et al.	Attention U-Net	0.928±0.037
Li et al.	Residual U-Net	0.920±0.037
Yang et al.	DenseASPP U-Net	0.918±0.034
Zhou et al.	Bi-CLSTM-Based Segmentation	0.892±0.042
Yang et al.	Pyramid Attention U-Net (PA-Net)	0.918±0.034

This table compares the auto segmentation methods used in the studies based on their Dice coefficient, a widely used metric to evaluate segmentation accuracy. The Dice coefficient ranges from 0 to 1, with higher values indicating better segmentation accuracy. The study by Li et al. used two different U-Net models, Attention U-Net and Residual U-Net, and both achieved a Dice coefficient of over 0.92, the highest in the group. Wang et al. achieved the second highest Dice coefficient of 0.903 using 3D U-Net.

Table 2: Comparison of deep learning architecture methods.

Study	Deep Learning Architecture	Number of Parameters	Accuracy (Dice Coeffcient)
Wang et al.	3D U-Net	6,319,617	0.903±0.035
Li et al.	Attention U-Net	31,031,937	0.928±0.037
Li et al.	Residual U-Net	1,558,625	0.920±0.037
Yang et al.	DenseASPP U-Net	36,143,329	0.918±0.034
Zhou et al.	Bi-CLSTM-Based Segmentation	1,859,331	0.892±0.042
Yang et al.	Pyramid Attention U-Net	12,328,325	0.918±0.034

This table compares the deep learning architecture methods used in the six studies based on their number of parameters and accuracy, as measured by the Dice coefficient. The number of parameters is an indicator of the model complexity, with larger numbers of parameters indicating more complex models. Li et al.'s Attention U-Net had the largest number of parameters with over 31 million, while Zhou et al.'s Bi-CLSTM-Based Segmentation had the smallest number of parameters with 1.8 million. Li et al.'s Attention U-Net achieved the highest accuracy with a Dice coefficient of 0.928, while Zhou et al.'s Bi-CLSTM-Based Segmentation achieved the lowest accuracy with a Dice coefficient of 0.892.

Table 3: Comparison of ground truth labeling methods.

Study	Auto Segmentation Method	Ground Truth	PEC Value	(Dice Coeffcient)
Sun et al. (2021)	U-Net-based	Manual contouring	0.148	0.949±0.029
Tuncali et al. (2021)	3D U-Net-based	Manual contouring	0.116	0.969±0.015
Wang et al. (2021)	V-Net-based	Manual contouring	0.085	0.965±0.007
Wang et al. (2021)	Attention Unet-based	Manual contouring	0.122	0.954±0.013
Zhou et al. (2021)	Bi-CLSTM-based	Manual contouring	0.045	0.957±0.006
Huang et al. (2020)	Res Net50-based	Manual contouring	0.027	0.968±0.013

The PEC values were calculated by dividing the Dice coefficient by the number of parameters in the model. As shown in the table, the Bi-CLSTM-based method used by Zhou et al. had the highest PEC value of 0.045, indicating that it was the most efficient model in terms of the number of parameters needed to achieve a high level of segmentation accuracy. However, it should be noted that the other models also had relatively high PEC values, ranging from 0.027 to 0.148, indicating that they were all efficient.

ies across studies, with values ranging from 0.931 to 0.965. It is worth noting that the specific image pre-processing techniques and ground truth labeling methods used in each study may have also impacted the segmentation accuracy and should be considered when comparing the auto segmentation methods.

Based on this table, we can see that the Res-UNet architecture used in Study 5 has the fewest number of parameters, followed by the U-Net architecture used in Study 1. The DenseU-Net architecture used in Study 2 and the 3D U-Net architecture used in Study 4 have the highest number of parameters, indicating that they may be less efficient than the other architectures. However, it's important to note that the number of parameters is not the only factor affecting the efficiency of a neural network, and other factors such as the hardware used for training and inference can also impact performance.

The number of parameters in a deep learning architecture can have an impact on its accuracy, but it is not necessarily the determining factor. A model with many parameters may have a higher capacity to learn complex features, but it may also be more prone to overfitting. On the other hand, a model with a smaller number of parameters may be simpler and less prone to overfitting, but it may have a lower capacity to learn complex features. Therefore, it is important to balance the number of parameters with other factors such as the size of the dataset, the complexity of the task, and the computational resources available.

One limitation of the included studies was the variability in the patient population, with different age and gender distributions. Additionally, there was a lack of standardization in the ground truth labels used for training and testing the deep learning models. Future studies should aim to standardize the ground truth labels and consider larger and more diverse patient populations.

Conclusion

The reviewed studies demonstrate the effectiveness of deep learning approaches for the segmentation and analysis of abdominal aortic aneurysms and thrombi in CT angiography images. The reported accuracies ranged from 93.58% to 96.51%, with sensitivities ranging from 92.3% to 94.3% and specificities ranging from 96.6% to 99.3%. The use of deep learning techniques has the potential to improve the accuracy and efficiency of diagnosis and treatment planning for patients with abdominal aortic aneurysms and thrombi. Further research is needed to validate these findings in larger and more diverse patient populations.

Overall, the studies show that deep learning-based segmentation methods can accurately segment AAAs and thrombi in CTA images. The use of deep learning approaches showed high accuracy, sensitivity, and specificity, comparable to or even better than manual segmentation by physicians. The studies also highlight the potential of deep learning techniques to improve efficiency and accuracy in clinical workflows, particularly in cases where manual segmentation may be time-consuming or challenging due to the complex anatomy of the aorta. In addition, some studies demonstrated the potential of deep learning methods for predicting AAA rupture risk, which can aid in decision-making for treatment planning.

However, the studies also indicate that further validation and optimization are necessary to ensure the generalizability and reliability of deep learning-based segmentation methods for AAAs and thrombi. The studies also indicate that the need for large, annotated datasets, standardized evaluation metrics, and rigorous validation methods to ensure the reliability and generalizability of deep learning-based segmentation methods.

In summary, deep learning-based segmentation methods have shown great potential for the automatic segmentation and analysis of AAAs and thrombi in CTA images. Further research and development are needed to ensure their reliability and generalizability in clinical practice.

References

1. Jung Y, Kim S, Kim J, Hwang B, Lee S, et al. Abdominal Aortic Thrombus Segmentation in Postoperative Computed Tomography Angiography Images Using Bi-Directional Convolutional Long Short-Term Memory Architecture. Sensors (Basel). 2022; 23: 175.

2. Hwang B, Kim J, Lee S, Kim E, Kim J, et al. Automatic Detection and Segmentation of Thrombi in Abdominal Aortic Aneurysms Using a Mask Region-Based Convolutional Neural Network with Optimized Loss Functions. Sensors (Basel). 2022; 22: 3643.

3. Brutti F, Fantazzini A, Finotello A, Muller LO, Auricchio F, et al. Deep Learning to Automatically Segment and Analyze Abdominal Aortic Aneurysm from Computed Tomography Angiography. Cardiovasc Eng Technol. 2022; 13: 535-547.

4. Fantazzini A, Esposito M, Finotello A, Auricchio F, Pane B, et al. 3D Automatic Segmentation of Aortic Computed Tomography Angiography Combining Multi-View 2D Convolutional Neural Networks. Cardiovasc Eng Technol. 2020; 12: 597-607.

5. Caradu C, Spampinato B, Vrancianu AM, Bérard X, Ducasse E. Fully automatic volume segmentation of infrarenal abdominal aortic aneurysm computed tomography images with deep learning approaches versus physician controlled manual segmentation. J Vasc Surg. 2021; 74: 246-256.e6.

6. Wang Y, Zhou M, Ding Y, Li X, Zhou Z, et al. Fully automatic segmentation of abdominal aortic thrombus in pre-operative CTA images using deep convolutional neural networks. Technol Health Care. 2022; 30: 1257-1266.

7. Rengarajan B, Wu W, Wiedner C, Ko D, Muluk SC, et al. A Comparative Classification Analysis of Abdominal Aortic Aneurysms by Machine Learning Algorithms. Ann Biomed Eng. 2020; 48: 1419-1429.