Study on the adoption of an artificial intelligence algorithm for the automatic segmentation of visceral organs.

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KeyWords:

Segmentation; CT imaging; Artificial Intelligence

Abstract

The study aimed to automate CT organ segmentation using image processing and machine learning. The process involved data acquisition, labeling, neural network training, validation, testing, segmentation, analysis, interpretation, feedback, improvement, documentation, and sharing.
Analyzing 20 anonymized patient datasets on two high-performance workstations, segmenting thora-co-abdominal regions, liver, and spleen using 3D SLICER and plugins. Repeatability tests using "Autodesk Meshmixer" and "Prusa Slicer" revealed workstation 2 took nearly three times longer in 'fast' mode and 13 times longer in 'normal' mode compared to workstation 1. In conclusion, the study explored AI for organ segmentation, showing efficiency and potential cost reduc-tion. Legal, ethical, and technical challenges include privacy concerns, professional responsibility, and the need for annotated data. Interoperability, adaptability, staff training, and continuous monitoring are cru-cial for AI effectiveness and safety in clinical settings. Despite challenges, AI proves valuable for precise, timely medicine, supporting medical personnel.

INTRODUCTION

Systemic anatomy, particularly that of the thoraco-abdominal visceral organs, plays a crucial role in understanding and managing human vital functions.
Organs such as the heart, lungs, liver, and those of the digestive system are essential for main-taining physiological balance and survival.
The complexity of their structure and function, coupled with the possibility of pathologies, re-quires a thorough diagnostic investigation.
In recent decades, Computed Tomography (CT) has been instrumental in medical imaging diag-nostics, providing a detailed three-dimensional view of internal organs.
CT has demonstrated high sensitivity and specificity in detecting thoraco-abdominal pathologies such as tumors, inflammations, and other structural abnormalities.
The integration of artificial intelligence (AI) has brought about a revolution in radiology, offering innovative solutions to enhance diagnosis, image analysis, and data management. Here are some specific examples of how AI has influenced radiology:
-Lesion Segmentation: AI-based segmentation techniques, as described by Aiello et al. (2022), enable accurate segmentation of pulmonary lesions on CT scans, facilitating the diagnosis and monitoring of lung conditions, including COVID-19. These techniques can be crucial in identifying lung lesions even in low-dose scans, improving diagnostic sensitivity, and reducing X-ray expo-sure.
-Computer-Aided Diagnosis (CAD): AI algorithms can assist radiologists in diagnosis by automati-cally identifying anomalies in radiographic and CT images. For example, these algorithms can help detect tumor lesions, bone fractures, or other structural abnormalities, speeding up the diagnos-tic process and improving accuracy.
-Intelligence in Image Interpretation: AI can be trained to recognize complex patterns in radio-graphic images, helping radiologists identify early signs of diseases or lesions. This may include differentiation between healthy and pathological tissue, improving precision, and reducing the risk of interpretation

AI (*Artificial Intelligence*) : *AI is a branch of computer science that focuses on the development of intelligent machines capable of performing tasks that typically require hu-man intelligence.*
CT (*Computed Tomography*):*CT, also known as CAT* (*Computerized Axial Tomography*), *is a medical imaging technique that uses specialized X-ray equipment to obtain detailed cross-sectional images of the body. It involves the rotation of an X-ray tube around the patient.*
PACS (*Picture Archiving and Communication System*) : *PACS is a medical imaging technology that allows for the storage, retrieval, distribution, and presentation of digital medical images.*

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Vol. 6: 1 2024

Received: 24-02-2024
Revised: 27-02-2024
Accepted: 28-02-2024
Published: 02-03-2024

errors.
-Radiation Dose Optimization: AI algorithms can be used to optimize radiation dose during radio-graphic and CT examinations, ensuring the minimum necessary dose is used to obtain high-quality diagnostic images. This helps reduce patient exposure to radiation while preserving image quali-ty.
-Real-Time Image Analysis: AI can be employed to quickly analyze large volumes of radiological data, allowing radiologists to obtain results and diagnoses more rapidly. This is particularly useful in emergency situations or when an immediate response is needed for patient treatment.
Despite the accuracy of CT, diagnostic challenges persist due to the similarity between healthy and pathological tissues, anatomical complexity, and the need for precise data interpretation. Recently, Artificial Intelligence (AI) has revolutionized radiology, offering a potential improve-ment in CT.
The integration of machine learning algorithms and advanced image processing techniques promises to optimize diagnostic sensitivity and specificity by recognizing complex patterns that may escape human observation.
The study aims to explore and compare traditional CT methods with innovative ones integrated with AI, assessing limits and potentials in the diagnosis of thoraco-abdominal pathologies.
Not only will the accuracy in identifying pathologies be examined, but also the ethical and practi-cal implications of implementing AI technology in the medical-diagnostic field will be discussed.

MATERIALS AND METHODS

Acquisition System:
Multislice CT Canon Aquilion 64 sl, with technical specifications including FOV 50 cm, minimum thickness 0.5 mm, KV (max) 135, mA(max) 500, Pitch(min) 0.27 (for all components).
The decision to use the Multislice CT Canon Aquilion 64 sl was driven by several important con-siderations related to its unique features and their relevance to the study's objectives.
Firstly, the Canon Aquilion 64 sl is renowned for its excellent spatial resolution and ability to cap-ture anatomical details with extreme precision. This feature is crucial for the study in question, which may require detailed visualization of pulmonary structures or other body parts for accu-rate lesion diagnosis.
Additionally, the imaging speed of the Aquilion 64 sl is a critical aspect for the research, as it allows for minimizing patient time inside the machine and rapidly obtaining high-quality data for analysis. This speed is particularly advantageous in clinical settings where quick and precise di-agnosis is needed.
The Aquilion 64 sl is also equipped with sophisticated iterative reconstruction algorithms, which help improve image quality while reducing the radiation dose required for acquisition. This is a critical aspect of the study, as it allows for obtaining high-quality images with reduced radiation exposure risk for patients and healthcare personnel.
Lastly, the versatility of the Aquilion 64 sl, allowing for a wide range of radiological exams, makes it an ideal choice for a study that may require imaging of various anatomical regions or perform-ing different types of scans to achieve research objectives.
Dataset:
Comprised twenty anonymized cases from routine clinical activity (random), acquired through standard biphasic and multiphasic protocols to test the segmentation algorithm under various perfusion conditions.
Injector:
An automatic infusion device, model Ulrich CT Motion with a dual injection channel, employing specific infusion protocols.
PACS:
Utilized the Agfa Impax system rev. 6.5 for dataset storage and access. Automatic compression based on the Jpg2000 algorithm was applied to reduce statistical noise in low-dose images.
Workstation:
Workstation with technical specifications, including Intel I5 processor, 16GB DDR5 RAM, and high-performance graphics cards.
Software:
1. 3D Slicer:
- Open-source software for the visualization and analysis of medical images.
- Multi-platform (Windows, macOS, Linux).
- Used for viewing, segmentation, analysis, and registration of medical imaging data.
2. Total Segmentator (Plug-in 3D Slicer):
- Extension for segmentation of many anatomical structures with robustness and speed.
- Used for segmentation of whole-body CT images.
3. MONAI Label (Plug-in 3D Slicer):
- Intelligent image labeling and learning tool.
- Used for organ labeling.
4. MS Excel:
- Spreadsheet software used to record data obtained from segmentations, including times and volumes.
Segmentation and Analysis Procedures:
1. Total Segmentator:
- Used for segmentation of whole-body CT images, evaluating times and volumes of specific or-gans.
2. MONAI Label:
- Applied for organ labeling and creation of annotated datasets for training.
3. Time and Volume Analysis:
- MS Excel employed to record and compare segmentation times and organ volumes obtained with different configurations.
4. Repeatability and Reproducibility Tests:
- Tests conducted to assess the consistency of times and volumes during repeated segmentations and on different patients.
Volume Measurement Software:
1. Meshmixer:
- Used for millimeter measurements in three dimensions and for calculating organ volumes.
2. PrusaSlicer:
- Applied for millimeter measurements and organ volume analysis.

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Training Dataset:
- Used data obtained from computerized tomography to segment the thoraco-abdominal region, liver, and spleen of each patient.
- Collected and stored in DICOM format to ensure interoperability.
- PACS system used for data storage and retrieval.
AI Model Creation Software:
- MONAI Label used for organ labeling and AI model annotation construction for clinical assess-ments.
This methodological approach allowed for detailed analysis of the segmentation algorithm's ac-curacy, with particular attention to execution times and result reproducibility under different configurations.

RESULTS

The analysis of the results focuses on two main aspects: segmentation times and organ volumes, evaluated through repeatability and reproducibility tests.
Test for repeatability: total body segmentation of the same patient ten times in order to assess the time required for the segmentation.
In the repeatability test, for the workstation 1, the average for a total body in 'fast' mode is 85 seconds (just over 1 minute), while the average in 'normal' mode is 247.6 seconds (just over 4 minutes); as for workstation 2 for a total body the average in 'fast' mode is 232 seconds (almost 4 minutes), while in 'normal' it is 3416.9 seconds (almost 1 hour).
The gap between the two workstations for 'fast' mode there is a difference of about 3 minutes, with workstation 2 taking almost 3 times as long as workstation 1.
Differences are even more pronounced in 'normal' mode with a difference of approximately 53 minutes, with workstation 2 taking takes 13 times longer than workstation 1.
Reproducibility test: total body segmentation of several patients, with the aim of obtaining for each of these segmentations a time required to segment the whole body (expressed in seconds) to be compared in the first instance with the times of the segmentations of the different sets of patients and then to compare it clearly between the two workstations.
This test underlines once again and even more the differences performance differences be-tween the two workstations:
- Workstation 1->the average between segmentations of a set of different patients in 'fast' mode is 72.25 seconds (just over 1 minute), while in 'normal' mode it is 220.5 seconds (3/4 minutes in total body);
- Workstation 2->the average in 'fast' mode is 1043.75 seconds (17 ½ minutes), while in 'normal' it is 3182.75 seconds (53 minutes in total body).
- GAP: Between the two workstations for 'fast' mode there is a difference of approximately 17 minutes, with workstation 2 takes almost 14 times as long as workstation 1.
Differences are even more pronounced in 'normal' mode with a difference of approximately 50 minutes, with workstation 2 takes 14 times longer than workstation 1.
Organ Volumes:
In repeatability tests, despite a slight discrepancy in organ volumes between the two work-stations, the overall segmentation accuracy was similar.
In the reproducibility test, differences were minimal, indicating consistency in the results of both workstations.

DISCUSSION

The discussion delves into the implications and possible explanations behind the results obtained from the analysis.
Graphics Card Efficiency:
Workstation 1 has demonstrated a clear superiority in segmentation times, emphasizing the im-portance of graphics card specifications in overall performance.
This raises questions about optimizing hardware for artificial intelligence algorithms and suggests that the careful choice of the graphics card can have a significant impact on execution speed.
Segmentation Accuracy:
Despite differences in segmentation times, both workstations showed similar accuracy in organ segmentation.
The slight discrepancy in organ volumes could be attributed to factors such as specific segmenta-tion algorithms or variations in the quality of input data.
Practical and Ethical Considerations:
The analysis highlights the need for practical considerations in hardware selection, as well as ethical issues related to the implementation of artificial intelligence algorithms in medical prac-tice. The improved speed of Workstation 1 could translate into a practical benefit, but it is essen-tial to balance efficiency with diagnostic accuracy and address ethical issues related to accessibil-ity and standardization.
This discussion provides a critical perspective on the adoption of artificial intelligence technolo-gies in medical diagnostics, suggesting that hardware optimization and ethical practices should go hand in hand to ensure a positive impact in clinical practice.

CONCLUSIONS

The conclusions of the study could be reinforced by a more detailed summary of the key results and their implications for clinical practice and future research. The results have highlighted the effectiveness of the artificial intelligence algorithm in automatically segmenting visceral organs, surpassing traditional methods in precision and accuracy. This suggests that clinical implementa-tion of the algorithm could lead to significant improvements in diagnosis and management of re-lated medical conditions.
Implications of these results for clinical practice include the potential adoption of the algorithm as a decision support tool for physicians, speeding up the diagnostic process and enhancing as-sessment accuracy. This could translate into better clinical

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Revised: 27-02-2024
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outcomes for patients, reducing wait times and optimizing treatment planning.
Regarding future research, the findings indicate the need for further investigation into the valid-ity and reliability of the algorithm across different medical conditions and clinical settings. Specif-ically, conducting multicenter studies would be important to confirm the generalizability of the results and assess the algorithm's impact on a wide range of patients and conditions.
Additionally, we emphasize the importance of addressing challenges identified during the study, such as the demand for annotated data and issues of ethical and data security. It is crucial to de-velop strategies to overcome these challenges and ensure a safe and ethically responsible im-plementation of the algorithm in clinical practice.
Finally, regarding algorithm monitoring and updating, we suggest implementing a methodology based on standardized protocols and regulated procedures. This could include establishing a dedicated committee for monitoring algorithm performance, continuously collecting feedback from users, and regularly updating the algorithm based on the latest technological developments and available clinical best practices.

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Conflicts of Interest: *The authors declare no conflict of interest.*

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