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Management and Application of AI to DICOM Image Processing: A Systematic Mapping Literature Review

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Abstract. Artificial intelligence (AI) has the potential to bring unprecedented benefits to humankind. Therefore, it is worth investigating how to maximize these benefits while avoiding potential pitfalls. Given this context, the first task necessary to assess the potential of this approach is to understand the management landscape and the application of AI to DICOM image processing. In this case, the researchers employ a systematic mapping review. This paper presents this process and its main findings. 35 studies have been selected from a total of 154 analyzed. From them, in addition to obtaining a clear view of the application of AI to DICOM images, we can also conclude that pre-trained AI algorithms are used in a higher amount than non-trained algorithms in terms of DICOM image usage.

Keywords: Artificial Intelligence · algorithms · DICOM · pre-trained · segmentation

1 Introduction

AI algorithms in medical image processing have revolutionized how doctors study and diagnose diseases. Deep neural networks, also known as convolutional neural networks (CNNs), are used to extract complicated information from DICOM pictures. AI is used for precise segmentation of anatomical features in DICOM pictures, as well as illness identification. Image artifacts can be corrected, noise reduced, and resolution improved, resulting in crisper and more detailed images for further analysis and diagnosis. AI algorithms are not designed to replace physicians, but rather to serve as a support tool.

To analyze and summarize the current state of research on this subject, this paper gives a complete systematic mapping of the application of artificial intelligence algorithms to DICOM imaging. The primary goal of this systematic mapping is to conduct a thorough examination of the scientific literature to discover and categorize the many uses of artificial intelligence algorithms in DICOM imaging. The results of this comprehensive mapping will provide an up-to-date overview of the research done too far in applying artificial intelligence algorithms to DICOM pictures. This paper presents the mapping process, its results, and the main findings obtained from them. The rest of the paper is structured as follows: Sect. 2 describes the SMP process, Sect. 3 presents the main results; finally, the work closes with some conclusions.

2 The Systematic Mapping Process

In this work we are developing a SMP (Systematic Mapping) with a software engineering strategy, so the first step is to define the main objective of the review and the second one is to develop it. The main objective of this review is to compile and analyze the existing studies related to the application of Artificial Intelligence in the health sector, specifically, to DICOM (Digital Imaging and Communication in Medicine) images, considering:

- The different applications that Artificial Intelligence has on DICOM images.
- The different types of Artificial Intelligence algorithms that can be applied to different DICOM images.
- Whether the applied algorithms are previously trained and their feedback has been obtained.

Once the objective has been defined, it is necessary to complete the next two phases: planning and realization. In these phases, a set of mapping questions (MQ) will be defined to help answer the research questions (RQ), which facilitate the achievement of the mapping objective.

2.1 Planning Stage

The first phase of the process is the planning of the review to be performed. This phase includes several steps which are:

- Define research questions (RQ) that will be applied to all studies and thus be able to extract data more easily.
- Define the search strings, including the terms that will be most relevant to the SMP.
- Describe the sources where the studies for the SMP will be searched.
- Establish the selection criteria, i.e., define the considerations regarding the exclusion of a study from the review.
- Define quality guidelines for evaluating the selected studies.

2.1.1 The Research Questions

To carry out the review of the main objective defined in the introduction, the following research questions (RQ) have been formulated:

- RQ1. What are the main approaches used in Artificial Intelligence applied to DICOM images?
- RQ2. What are the benefits of applying previously trained Artificial Intelligence algorithms to DICOM images?
- RQ3.What kind of algorithms are applied to DICOM images and what are they used for?

- RQ4. What are the most relevant authors, sources (journals, conferences, books) and locations?

And, by answering these questions it will be possible to gather all the necessary information and, therefore, reach the objective of the SMP.

2.1.2 The Search String

Once the RQs have been defined, the search string needs to be established. This string should include all those terms that will be used in the search process to arrive at answers to the RQs. In this case, the terms that have been selected have been:

- “DICOM images” or “Digital Imaging and Communication in Medicine” as the context in which we would like to know how Artificial Intelligence is applied.
- “Artificial Intelligence” or ‘"AI” as part of the search context, using both terms because the latter is an acronym for the former.
- “Algorithms” as part of the search context since we are interested in which algorithms are applied.
- “Trained Algorithms”} as part of the search context since we are interested in looking for algorithms that are already trained.

Using these terms and Boolean operators combinations (AND, OR), we will define a search string that may vary depending on the source. The generic search string used is the following:

(“DICOM images” OR “Digital Imaging and Communication in Medicine”) AND (“Artificial Intelligence” OR “AI”) AND (‘"Algorithms” OR “Trained Algorithms”).

2.1.3 Source Selection

The next choice to make is to select where to look for the studies that will be part of the SMP. This may determine the scope of the mapping. In this case, five of the most popular and comprehensive libraries will be considered with the topics of this study in mind:

- IEEE Digital Library (https://ieeexplore.ieee.org/)
- ACM Digital Library (https://dl.acm.org/advsearch.cfm)
- Springer Link (https://link.springer.com)
- PubMed (https://pubmed.ncbi.nlm.nih.gov)
- SCOPUS (https://www.scopus.com/)

The reason for applying these sources is that they are very reliable as they include many journals and conferences and, for example, PubMed is specialized in a health context.

2.1.4 Definition of the Inclusion and Exclusion Criteria

Once the sources to be searched have been established, it is necessary to define criteria to decide which studies can be discarded, based on their metadata, title and abstract. Only the included papers will be used to continue with the review process. For example, we can decide to exclude those papers written before 2015, or those papers that do not include DICOM or Digital Imaging and Communication in Medicine as any of their keywords. Thus, for this SMP, the inclusion criteria are:

- IC1. The study must be written in English.
- IC2. The study was published after 2015.
- IC3. The study was published before the end of 2022.
- IC4. The study was published in a peer-reviewed journal or conferences.

And the exclusion criteria are:

- EC1. Studies whose document is not accessible.
- EC2. Studies that are not papers.
- EC3. Studies that were not published in a peer-reviewed journal or conference.
- EC4. Studies that address the topics of this study and include the search terms, but do not answer the research questions (RQs).
- EC5. Studies that, in addressing some of the research topics, merely redefine concepts.

2.1.5 Checklist for Quality Assessment

The next step in the process, once the studies that meet the inclusion criteria have been included, is to check the quality of the studies and retain only those with acceptable quality. For this purpose, a checklist of 11 questions has been defined. All questions, except the last one, can be answered with "YES", "PARTIALLY" or "NO" and each answer is assigned a score (1, 0.5 or 0, respectively). As for the last question, it will be scored with a value between 0 and 10. Therefore, the checklist items are:

- QC1. Is the paper based on research or is it merely a report based on expert opinion?
- QC2. Are the objectives of the paper correctly stated?
- QC3. Does the study adequately describe the research?
- QC4. Does the design of the paper address the objectives of the investigation?
- QC5. Has the sample selection been correctly made in accordance with the research objectives?
- QC6. Is there a control section and a section to compare the results?
- QC7. Is the information collected in an adequate way to address the research topic?
- QC8. Are the results adequately described and discussed?
- QC9. Does the work have an application to research or practice?
- QC10. Is the analysis of the data sufficiently rigorous and supported by the literature?
- QC11. Does the paper describe the application of Artificial Intelligence algorithms to DICOM images or describe applications of Artificial Intelligence to DICOM images?

2.2 Conducting Stage

The second phase that occur in the SMP is the realization phase, which consists of the implementation of the results of each of the steps of the planning phase. The different steps of this stage can be seen in the Fig. 1. A part of them is grouped in the PRISMA model (Preferred Reporting Items for Systematic Reviews and Meta-Analysis). The steps included in the realization are:

- Identification. This step includes the search process, which requires the application of the search string in the sources that have been defined in the planning and, the import of studies. Duplicate studies are also eliminated during this step.
- Screening. This step applies the inclusion and exclusion criteria and then selects the articles that may be of interest to the research.
- Eligibility. This step includes reviewing the reference list of articles to find others that could also be included in the analysis, as well as applying the quality assessment checklist.
- Content. Definition of the specific documents to be analyzed in the next two steps, i.e., to be used for data extraction and analysis.
- Data extraction. With the selected items, the questions defined in the data extraction stage of the planning phase are answered allowing to gather the relevant information for the analysis.
- Data analysis. Presentation of the results and determination of how the research questions (RQ) defined at the beginning can be answered.

These steps can be grouped in a way that represents the results of the realization by means of a PRISMA flow diagram, as shown in Figure. This diagram shows that once the identification phase (which includes searching, importing, and eliminating duplicate studies) was completed, there were a total of 154 studies. In the screening phase (applying the inclusion and exclusion criteria) the studies were reduced to 74. Finally, in the eligibility phase, only a few new papers were added once the references of those already selected were studied and the quality assessment list was applied, resulting in 35 total papers to be analyzed.

3 Data Results and Data Analysis

This section shows the results obtained when answering the mapping questions to extract the necessary data. It should be noted that this has only been done with the articles selected once the inclusion and exclusion criteria and the quality control checklist have been applied.

3.1 RQ1. What Are the Main Approaches Used in Artificial Intelligence Applied to DICOM Images?

There are several approaches used in Artificial Intelligence that are applied to DICOM images, such as:

- Convolutional Neural Networks (CNN): convolutional neural networks are a type of deep learning model specially designed for image processing. These networks are composed of convolutional layers that can extract specific features from images by applying convolutional filters. CNNs have been widely used in the classification, detection, and segmentation of pathologies in DICOM images [2–5].
- Deep Learning: Deep learning is a branch of AI that uses multi-layered artificial neural networks to learn and extract complex features from data. In the context of DICOM imaging, deep learning is applied using deep neural network architectures, such as

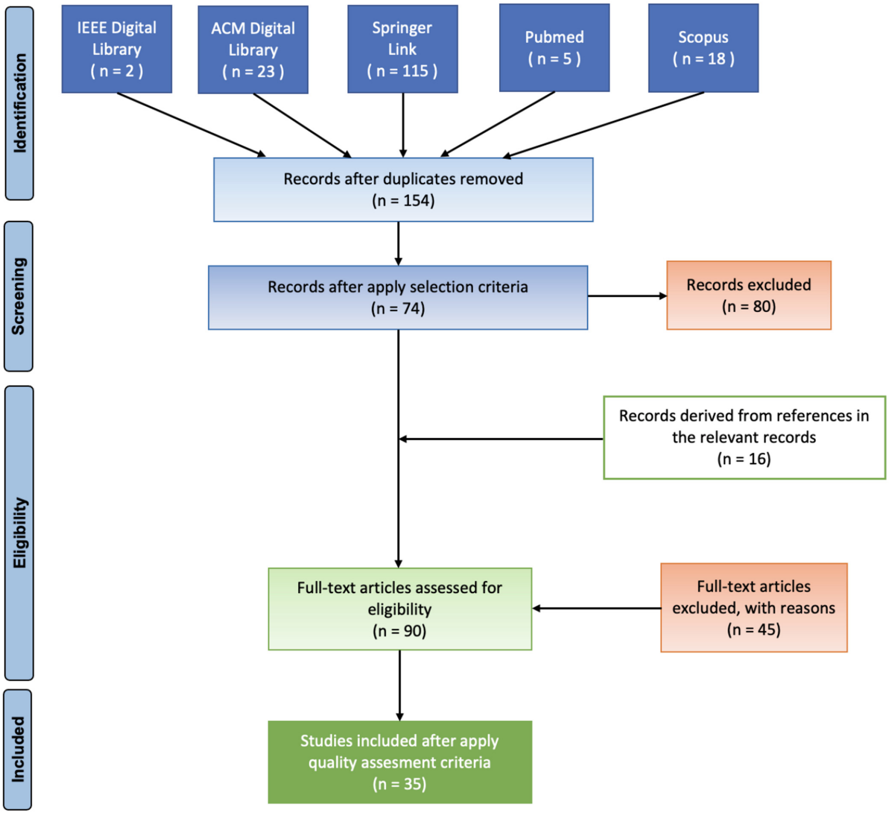

Fig. 1. The Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) flow diagram adapted from Reference [1]

deep convolutional neural networks (DCNN) and generative adversarial networks (GAN), for tasks such as anomaly detection, segmentation of anatomical structures, and image quality improvement [6–13].

- Transfer Learning: Transfer learning is a technique that allows taking the knowledge and experience acquired in a specific task and applying it to a related task. In the context of DICOM images, this involves using AI models previously trained on large general datasets (e.g., ImageNet) and adapting them for specific tasks, such as disease classification or tumor detection in DICOM images.
- Semantic Segmentation: Semantic segmentation aims to identify and classify individual pixels in an image into different categories. In the context of DICOM images, semantic segmentation is used to delimit and segment specific anatomical structures or regions of interest in the image, such as organs, tumors, or blood vessels. Approaches based on convolutional neural networks and deep learning models have proven to be effective in semantic segmentation of DICOM images [3, 13–21].
- Feature Analysis: This approach focuses on the extraction and analysis of specific features from DICOM images for diagnostic and disease detection tasks. It may

involve image processing techniques such as texture extraction, morphological feature computation or statistical feature measurement. These features are used as inputs for AI algorithms, such as classifiers or regression models, to make diagnoses or clinical predictions [5, 22–26].

Importantly, the combination of different approaches and techniques can be used depending on the specific task and clinical context in which they are applied.

3.2 RQ2. What Are the Benefits of Applying Previously Trained Artificial Intelligence Algorithms to DICOM Images?

Pre-trained AI algorithms have been rigorously tested and validated, ensuring accurate and reliable results. Experience helps AI algorithms detect complex patterns and subtleties that limited training may miss. AI models trained on diverse datasets generalize better to new situations and tasks, adapting easily to a wide range of problems and data without added training. Pre-trained AI algorithms benefit from continuous improvements and updates from an active development community, enhancing their performance and keeping them current with AI advancements.

On the other hand, pre-training in segmentation involves using a pre-trained model for a task and modifying it for a related, but different problem. Transfer learning involves using a pre-trained model and making small changes to apply it to a similar, but new, task. There are three approaches to this process: replacing and retraining only the output layers, refining a part of the model, and refining the entire model. The basic idea is that the pre-trained model will be taken and, subsequently, it will be refined to specialize it for the data to be used. There are three approaches to this process: replacing and retraining only the output layers, refining a part of the model, and refining the entire model [2, 18, 27].

3.3 RQ3. What Kind of Algorithms Are Applied to DICOM Images and What Are They Used for?

The Artificial Intelligence algorithms applied in most cases are segmentation algorithms. Segmentation is one of the general problems in the field of computer vision and consists in dividing a digital image (DICOM images, in this case) into several regions or groups of pixels, which are called segments. More specifically, segmentation is a per-pixel classification process that assigns a category to each pixel of the analyzed image. This general problem is broken down into specialized problems such as segmentation by color or segmentation by texture.

Clinical segmentation algorithms use atlas-based techniques to fit labeled reference images to new scans, but this may not account for postsurgical changes or anatomical variability between patients, leading to potential errors. Algorithmic segmentations still need manual editing, perform worse than human experts in clinical practice, and have not improved workflows. Evaluation is based on expert manual segmentation. To reduce variation in manual segmentation and achieve accurate results, multiple experts' segmentations are typically combined. One common strategy is to use a voting rule to determine the ground truth segmentation. This method ignores prior knowledge and limited reference patterns. CNNs are now widely used. A CNN mimics the human visual cortex's organization, using convolutional and fully connected layers. CNN's convolutional layer contains learned filter values, while the fully connected layers serve as the high-level reasoning component. Fully connected neurons connect to all previous layer activations in CNN-based vascular segmentation. CNNs extract esophageal microvessel features from NBI microscopy for SVM classification. CNNs extract features from retinal images, which are classified with an RF ensemble using a dictionary to reference different vascular patterns. The nearest feature vector from the dictionary is selected as the output vascular pattern using the nearest neighbor algorithm that works best for small data sets. ML approaches such as SVM and RF are better for pixel classification in datasets with low variability.

3.4 RQ4. What Are the Most Relevant Authors, Sources (Journals, Conferences, Books) and Locations?

This last question explores the authors, sources, and locations of the selected papers. Regarding the first question, we have a total of 254 authors. The most relevant (authors with more than one article in the selected group) were ***Olaf Ronneberger*** [10, 13] and ***Michelle Livne*** [10, 25].

Regarding the sources of the papers and considering the type of publications, we found that 34 of them were published in journals and the remaining two in congress conferences. This means that 95% of the publications were studies included in conferences and 5% were published in journals. If we analyze the different sources, the most relevant journals are the Journal of Digital Imaging, with a total of 4 articles [5, 28–30], European Radiology Experimental with a total of 3 articles [4, 26, 31] and the Journal of Applied Clinical Medical Physics, with a total of 2 articles [32, 33]. Considering the conferences the ones mentioned are the International Conference on Power, Energy, Control and Transmission Systems developed in 2022 [13] and MICCAI (Medical Image Computing and Computer-Assisted Intervention) developed in 2016 [34].

4 Conclusions

AI has the potential to improve diagnosis, personalize treatments, increase efficiency, reduce costs, prevent disease, improve access to care, and accelerate research and drug discovery. However, it is important to address ethical, privacy and regulatory challenges to ensure responsible and safe use of AI in healthcare. AI applied to DICOM imaging benefits medicine and radiology through improved diagnosis, efficiency, and speed of medical imaging analysis, reducing radiologists' workload and optimizing patient care. AI aids disease detection and monitoring by detecting and tracking diseases in DICOM images, including cancer, through pattern recognition for early treatment. AI can personalize treatment by analyzing clinical and DICOM data for precise recommendations. AI helps clinical decision making by analyzing DICOM images to detect anomalies, identify regions of interest, and provide image data to improve patient care.

Finally, the most important details of applying Artificial Intelligence algorithms to DICOM images are improved segmentation accuracy, time and resource savings, broad clinical applications, improved quality and consistency, and adaptability to different domains and modalities. Segmentation algorithms improve DICOM image segmentation accuracy, time and resource savings, broad clinical applications, improved quality and consistency, and adaptability to different domains and modalities. Additionally, DICOM image segmentation has clinical applications, aiding in treatment planning for radiotherapy, monitoring disease and treatment efficacy, and reducing human error and variability.

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