Pediatric Chest Radiography Research Agenda: Is Deep Learning Still in Childhood?

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Abstract—Despite advances in the acquisition of medical imaging and computer-aided support techniques, x-rays due to their low cost, high availability and low radiation levels are still an important diagnostic procedure, constituting the most frequently performed radiographic examination in pediatric patients for disease investigation while researchers are looking for increasingly efficient techniques to support decision-making. Emerging in the last decade as a viable alternative, deep learning (DL), a technique inspired by neuroscience and neural connections, has gained much attention from researchers and made significant advances in the field of medical imaging, outperforming the state-of-art of many techniques, including those applied to pediatric chest radiography (PCXR). Given the scenario and considering the fact that, as far as we know, there is still no mapping study on the application of deep learning techniques in PCXR images, we propose in this article a "deep radiography" of the last decade in this research topic and a preliminary research agenda that deals with the state of the art of applying DL on PCXR that constitute a collaborative tool for future researchers. Our goal is to identify primary studies and support the process of choosing and developing DL techniques applied to PCXR images, in addition to pointing out gaps and trends by drawing up a preliminary research agenda. A protocol is described in each phase detailing criteria used from selection to extraction and our set of selected studies is subjected to careful analysis to respond to the research form. Six basic sources were used and the synthesis, results, limitations, and conclusions are exposed.

Index Terms—Systematic mapping, Deep learning, Neural network, CNN, pediatric, X-ray, CXR, Chest, Lung, Thorax

I. INTRODUCTION

Children between 0 and 14 years old account for more than 25% of the world population [1], asthma affects 14% of children and has been increasing [2]. of all deaths among children under 5, 18% about 1.4 million a year, are caused by pneumonia and respiratory diseases are among the leading causes of child death in the world, affecting mainly residents in underdeveloped countries and with few resources [3].

Nowadays, it is impossible to address any pediatric pathology without the support and full analysis of a pediatric radiological study; however, many countries do not offer training dedicated to pediatric radiology and there is a global shortage of pediatric professionals, the causes range from low pay, the need to be always available and the high specialization required which does not attract new residents to include this sub-speciality in your main options [4].

Chest radiography (CXR) is not the most modern or accurate image diagnosis, and its use has several limitations, mainly related to its two-dimensional nature, which can lead to consolidation, adenopathy or complications masked by other anatomical structures, such as the heart, mediastinum, and diaphragm, can also lead to the problem of the sum shadows [5]. Nevertheless, in many cases, CXR is preferred over other more modern and accurate imaging diagnoses, such as magnetic resonance (MRI), computed tomography (CT), positron emission tomography (PET) and ultrasound (USG), as it provides high resolution, very small dose of ionizing radiation and is a low-cost test, with high availability and easy acquisition, even in peripheral regions, has been the initial test for the investigation or disposal of many diseases, even those that require other types of imaging or exams, about 350 million radiographs are performed on children alone, while 40% of all pediatric images consist of CXR [6], [7], [8].

Children are not to be considered as “little adults”. Thus, medical examinations in children will have to be different from those in adults. This is particularly true for paediatric X-ray examinations. Children differ from adults regarding: anthropometry, anatomy and physiology, psychology, radiation biology and radiation risk [9]. However, advances in pediatric radiology are always based on adult radiology and the protocols designed for them pose technical challenges when applied to children. In PCXR, for example, they are related to the smaller size of the examined area and to differences in certain functions, such as increased heart rate in neonates [8].

In addition, pediatric images, unlike images of adult patients, present other challenges, both for human and computational interpretation, because they are affected, for example, by the environment and equipment of acquisition not suitable for this audience, the cooperation of patients for positioning and maneuvers, insufficient inspiration, the greatest variation in anatomical structures and disease patterns, strict adherence to the ALARA principle (As Low As Reasonably Achievable) and the frequent presence of artifacts [10], [11], [12].

Another problem is the more limited number of studies and databases specifically related to pediatric chest images, such as cancer studies that, even with a growing body of literature on the subject, generally involve adult patients with specific knowledge in limited pediatrics [13], just to cite an example. Accurate diagnosis and attribution of the causes of a disease
are important to mediate its burden, implement appropriate prevention or treatment strategies and develop more effective interventions, which directly affect the efficiency and cost of treatment [5]. Therefore, there is an urgent need to develop agile and reliable software and hardware solutions to assist in this long, difficult and expensive task of diagnosing an increasing number of images, especially considering the limited number of experienced radiologists [14].

Over the past few decades, medical imaging techniques, such as CT, MRI, PET, USG and CXR, have been used for the early detection, diagnosis, and treatment of various diseases [15]. On the other hand, computational medical image analysis has become a prominent field of research at the intersection of Informatics, Computational Sciences, and Medicine, supported by a vibrant community of researchers working in academics, industry, and centers [16].

Machine learning methods have brought us a revolution in the field of computer vision, effectively solving many problems that have remained unresolved for a long time, and DL is now becoming the dominant approach, with very promising results in many areas extend to medical images.

Deep Learning (DL) is a sub-area of machine learning based on a model (neural net) that mimics the workings of the human brain in processing data and creating patterns for use in decision making [17]. This process where the computer acts as human experts in defining the feature sets to be extracted from the images is a complete paradigm shift that has been called by some at the end of the code [18].

Although it appeared in the 1980s [19], only recently has DL emerged as a promising computational technique for a wide range of research areas, including the medical field that has extensively used DL frameworks to detect multiple organs [20], [21], classification [22], and segmentation tasks [23], [24]. The most important reasons for this are advances in hardware development now available, especially in parallel processing of computers with Graphics Processing Units (GPUs), the development of new techniques designed for more efficient deep network training, and the availability of much more training data, allowing thus the use of its full potential [25], [18].

In [26] an interesting discussion is presented on the use of machine learning and artificial intelligence and its implications in radiology, ranging from the description of the types of learning to pointing out the challenges of its implementation in children’s images, which includes obstacles technical and regulatory aspects, as well as the opaque character of convolution neural networks (CNNs).

Litjens et al. [27] presented a broad review of the main concepts of DL pertinent to the analysis of medical images including CXR while Ginniken [13] in one other review study over the past fifty years of techniques applied to chest imaging showed that machine learning has made it the dominant technology for tackling CAD in the lungs, further indicating that DL even better results can be achieved.

Although several primary studies and few secondary studies have addressed PCXR in DL, as far as I know, none of them is a systematic mapping (SM). SM or scoping studies are used by many researchers on a number of areas using different guidelines or methods. These studies are designed to give an overview of a research area through classification and counting contributions in relation to the categories of that classification [28]. In addition, a well-documented SM study allows its reproduction by other researchers and further discussion of the topic under analysis.

Petersen et al. [29] proposed that a mapping study preceding a systematic review provides a valuable baseline. Kitchenham et al. [30], [31] observed multiple benefits in to do systematic maps such us time-savings for follow-up studies (e.g. due to reuse of study protocols); good overview of an area and the ability to identify research gaps; visualization of research trends; related work identification, etc. Kitchenham et al. [30], [31] also pointed out that it is important to have a well defined and reliable classification scheme.

This article provides a research agenda on a hot topic of great attention and interest (see Figure 1) and is based on a SM. A broad understanding of the application of DL techniques in pediatric chest X-ray images is presented highlighting its limitations, gaps, and future trends, it is supported by the selection and synthesis of closed primary studies on this subject.

![Interest over time](image)

**Fig. 1:** Interest over the last decade on "deep learning" and "chest x-ray". Numbers represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term.

The objective of this research agenda is therefore to contribute to the following items:

- point directly to the same conclusions as those verified in the reviews, with a summary based on the extraction of data from a comprehensive research form;
- support, through statistical data, the process of choosing and developing techniques DL applied to PCXR;
- point out the maturity level of techniques DL in each of the tasks applied to PCXR;
- indicate new bottlenecks and trends not yet pointed out by the reviews;
- provide a detailed SM process for allows possible reproduction, updates, and developments.
Our protocol based on described by Felizardo et al. [32] is described in each phase detailing criteria used from selection to extraction. This work includes studies published between 2010 and 2020 that were selected and subjected to careful analysis to respond to the research form. Six base sources were used and the synthesis, results, limitations, and conclusions are exposed.

The remainder of this paper is organized as follows. Section II describes related work to our proposal. Section III details the study protocol applied. Section IV presents the mapping study results from the extracted data and discusses the main observations found. Section V introduces a research agenda to gear future works on requirement patterns, and Section VI discusses the validity threats of this work and elaborates on their mitigation. Finally, Section VII suggests directions for future work.

II. RELATED WORK

Computational methods applied to CXR, especially in the field of computer vision, have been of great interest to the scientific community for a long time and more recently have improved their results through the use of DL techniques.

In this section, we present related work to the research proposed in this article.

Litjens et al. [27] analyzed the main DL concepts applied to the analysis of medical images and summarized more than 300 contributions, grouping them into image classification, object detection, segmentation, registration, and other tasks. The authors concisely demonstrate studies by area of application and the growing interest in the application of DL, such as the challenge of lung cancer detection on CXR of the Kaggle Data Science Bowl 2017, with US$1 million in prizes and more than one thousand participating teams. In the end, the authors noted DL will thus not only have a great impact in medical image analysis but in medical imaging as a whole.

Ginneken [18], in a rich article, reviews the literature about articles written last of 50 years and shows the evolution of various computational analysis techniques in chest imaging, from the rule-based to the DL and the point where the latter becomes the primary choice for image analysis. While observing various DL models, Ginneken discusses only the convnets. He explains why convolutional networks (convnets), while not as recent in image analysis techniques, only gained momentum from 2012 by pointing to the following reasons: (1) new techniques designed for more efficient deep network training; (2) availability of much more training data; (3) advances in parallel processing of computers with GPUs. Ginneken’s study adequately addresses DL and CXR among other subjects, but most of it is about CT images.

Likewise Koichiro Yasaka & Osamu Abe [33] presents a interesting review of DL and artificial intelligence in radiology with important highlights of various applications of DL that can aid with detection, diagnosis, staging, and subclassification of conditions in radiological images. They also point to the limitations of DL, such as the poor readability and interpretation of the characteristics and calculations that models use to make a classification, which makes it very difficult to resolve conflicts when the judgment of physicians or radiologists differs from models trained.

Lee et al. [34] in their review investigated the application of DL in CXR and CT images, highlighting their ability to deal with new information, an essential limitation in computer-aided detection. They also point out that while DL has shown impressive advances in many fields in the specific medical field, this technique is still in its infancy. According to the authors, several studies show that DL approaches have high potential to overcome the limitations of existing CAD systems, but there is still concern about this technology in terms of clinical application.

In a more recent study Tajbakhsh et. al [35] reviewed DL techniques applied specifically to the segmentation of medical images, raising questions mainly related to scarcity and quality of data set. They compare current methodologies, their benefits, and requirements, and ultimately recommend solutions to address each of the limitations raised.

Revisions of these authors, even if not systematic, are very important in helping other researchers understand issues such as the current state of the art in the area, its limitations, its potentials and future directions. Despite the undeniable value of this, in a systematic review there is more because, in addition to providing strong evidence on a specific topic, identifying, analyzing, interpreting and summarizing its evidence clearly and objectively, it also allows other researchers to reproduce, what is very much important [32].

Pande et al. in [36] provide a systematic review of computer-assisted detection of pulmonary tuberculosis on CXR digital. Its systematic review is one of the few available on this topic (if not the only one) which shows that efforts in this regard can make a valuable contribution.

The work by Pande et al. [36] covered about papers published between 1 January 2010 and 31 December 2015, used four sources PubMed, EMBASE, SCOPUS, and Engineering Village with a sensitive search strategy formulated in consultation with a medical librarian. In 455 articles returned from their four research sources, after applying inclusion and exclusion criteria, only 5 remained, which were used for extraction and synthesis. The extraction process was conducted by two independent reviewers using a standardized form. In the end, the authors point out that while limited by the small number of studies the evidence was that most had methodological limitations, the availability, and evaluation of only one software program, and generalization only for environments where PTB and HIV are less prevalent and therefore further research was needed.

While systematic reviews aim at synthesizing evidence, also considering the strength of evidence, SM are primarily concerned with structuring a research area [28].

Therefore, our review work differs from related reviews in two ways. First, it deals specifically with the application of DL on pediatric chest radiographs and secondly because it is the first research agenda supported by a study of SM applied to this topic, to the best of our knowledge.
III. STUDY PROTOCOL

Although SMs appear to be systematic reviews at many points, they are not the same, while the latter aim to synthesize evidence, also considering the strength of evidence, the SMs or scoping studies primarily concerned with structuring a research area and have as goals to give an overview of a research are through classification and counting contributions in relation to the categories of that classification [28], [37].

For conducted this SM we used the phases described by Felizardo et al. [32], it correspond: planning, conducting and publishing the results (see Figure 2). The StArt tool [38] was used as support the management of this systematic study also.

![Fig. 2: Phases and activities this study, adapted from [32]](image)

A. Planning

Before we begin planning phase we search for surveys and secondary studies related to our proposal and with objectives similar to those we had in mind. This step was performed for two purposes: first to check if there were any systematic reviews for the same research topic; second to evaluate the performance of the search string. Later, the results of this step were also used to guide a reverse snowballing technique which consists of evaluating the reference list of a relevant primary study, looking for other relevant primary studies [32].

The planning phase is an iterative process that goes from the objective statement to the evaluation, which is used to make possible adjustments if necessary.

1) Formulating the research questions: The definition of the purpose of our study is adapted from the PICO [39] criteria derived from medicine. The structure is described in Table I.

A Research Question (RQ) is the fundamental core of a research project, study, or literature review because this helps us focusing on what matters for the study in hand, guiding also the extraction phase of the process [40]. So we have defined our main research question as:

**RQ1: What is the state of the art of DL on PCXR images tasks?**

| TABLE I: PICO Analysis |
|-------------------------|
| **Population**          | Papers publication about DL applications on digital and conventional pediatric chest radiographs, considering all types of industries, systems and application domains. |
| **Intervention**        | Tasks on chest radiographs that use any DL solutions. |
| **Comparison**          | Not Applicable: Our intention is to classify the tasks performed on pediatric chest radiographs and the methods of DL used on them, no compare methods with other methods or processes. |
| **Outcome**             | Overview of the context of DL solutions on tasks of pediatric chest radiographs image processing, such as diagnosis, segmentation, enhancement, removal of artifacts, suppression of bone structures, reconstruction, recording, etc. |

The objective of this question is to identify the level of maturity of DL solutions applied to those canonical tasks in PCXR images (classification, detection, segmentation, registration, retrieval, image generation, enhancement), and to investigate possible tasks not achieved by DL solutions.

In addition, secondary research questions were used to better guide the other stages of this research. In this sense, the RQs that have been proposed for this SM is as follows:

**RQ2: Which tasks applied to pediatric chest radiographs imaging are most addressed by deep learning techniques?**

Its purpose is to explain which tasks applied about CXR are more covered with DL and which are uncovered. Tasks as classification, diagnostic, enhancement, segmentation, object recognition, localization, detection, prediction/prognostic to name a few.

**RQ3: What are the metrics used for assessment?**

Its purpose is to answer if exists metrics to assessment that are adopted how standard in each task.

**RQ4: What are the main datasets used in this research field and how are it organized?**

Its purpose to answer which datasets are available in this search field, whether they are public or private, what their sizes, CXR types, and whether they contain additional information like reports, other types of images, etc.

**RQ5: Did the work have ethics committee authorization?**

Its purpose is to know if the authorization of ethics committees, is a practice of this research field and reasons to be or not.

**RQ6: What are the neural network architectures used in the works?**

Its purpose is to answer if there is a dominant DL architecture about PCXR.

**RQ7: When and in which vehicle type was the articles published?**

Its purpose is to understand in which vehicles and what timeline the studies are published in the search field.
RQ8: What the details of types of data and process applied on DL technique?

Its purpose is to answer which training techniques, learning and processing approaches are used and whether the use of preprocessing steps is common.

RQ9: Which type of contribution results?

Its purpose is to identify how the contribution brought by the study is classified, algorithm, application, framework, product.

RQ10: Is there any international standard and is it applied?

Its purpose is to know if the studies in this field of research adopt any standard internationally and what is this standard.

RQ11: How is the study classified?

Its purpose is to identify how the studies are classified based on the classification proposed by Petersen et al [28].

RQ12: Which the research method adopted?

Its purpose is to identify which the research method are classified based on the classification proposed by Petersen et al [28].

2) Pilot Search and Search String: Responding to these RQs requires an appropriate research strategy based on the most relevant primary studies. To achieve this goal, the first step is to conduct a pilot search that finds a search sequence that balances the breadth and accuracy of the search with the relevance of the retrieved studies [32]. In this pilot research, the objectives are to define a search sequence that finds the gold-standard set of papers and also helps in defining a more consistent protocol.

With this balance in mind, we conducted our pilot search with a set of keywords, their synonyms and some acronyms related to the central research theme, an example this set was: deep learning, deep machine learning, deep inspection, artificial intelligence, artificial neural network, neural network, convolution network, convolution neural network, CNN, Recurrent neural network, RNN, deep belief network, DBN, autoencoder, chest, lung, breastplate, pulmonary, thoracic, x-ray, radiograph, radiogram, CXR, child, pediatric, infant, baby, toddler, newborn and neonate.

As suggested by [32] we reexamine our set of keywords from the pilot search results. This revaluation process was repeated several times and resulted in the following observations:

- Regarding the synonyms for deep learning, only neural network, CNN, and convolutional network represented some significance and gain to the number of articles returned, while the other terms did not represent any change.
- About chest only breastplate did not add results while the others represented return of more articles.
- About the terms child, infant, baby, toddler, newborn and neonate were thought to reduce the scope of research to pediatric radiographs, which was discarded due to the reduced number of articles returned in digital library Scopus for example, it was just one returned article.

At the end of the pilot research execution cycle and results evaluations, we come to the following set of keywords that were used in our search string, organized as follows:

- (deep learning OR neural network OR CNN OR convolution net AND (((chest OR lung OR thora) AND (x-ray OR radiogra)) OR CXR) AND (pediatr OR paediatr OR baby OR newborn OR child))

It is noteworthy that "neural network", "thora", "radiogra" and "child" are sub-string that closes for example respectively with recurrent neural network, convolution neural, artificial neural network; thoracic and thorax; radiogram and radiography; children and childhood, etc.

Other information important is that we had the help of a DL expert to define the synonyms for related terms and beyond this, we builded word clouds with the keywords and titles. This feature is very interesting because it makes it easier to find word frequencies, the more often they are used, the higher and bolder they are. This allows you to check for word adherence in the search string and make possible adjustments. Our final word cloud can be seen in Figure 3.

Once all the keywords were defined and our search string is complete then we constructed specific queries for each digital library. The specific queries are necessary because each library had different boundary characteristics, depending on its possibilities and limitations. For example, some of them do not allow the use of complete search strings; in others, it is necessary to complement these strings with simple textual searches.

Fig. 3: Clouds of words, keywords, and article titles returned from digital library research used in our study.
3) Search Strategy: Having defined our search string, we had to choose the ideal set of study sources applicable to our theme. This set of selection source followed a list of prerequisites as a view to following in this protocol:
- sources considered relevant for the deep learning and medical image areas;
- sources with a search mechanism available on the Web, and logical expressions support;
- sources that possible the result export with the compatible format with Start tool [41];
- sources that allow read access to studies that return; and
- sources that allow searches at least to the metadata title and abstract.

An important note is that all searches were carried out on the same day, on May 20, 2020, using automatic web mechanisms and queries defined from the search string.

As a result, the sources chosen for this SM include the following search engines and digital libraries: ACM Digital Library (configured to Guide to Computing Literature due to indexing a broader collection of papers), IEEE Xplorer, Scopus, and PubMed.

In our hands the selected sources and the set of keywords then we made the specific search to each digital library. The search was executed on the title, abstract, and keywords of the papers, except in PubMed library that did not allow search in keywords. The Table II shows the final queries in each one of the digital library used in this SM study.

4) Selection criteria: After final queries establish, were defined as the inclusion and exclusion criteria to use on the selection of primary studies. The exclusion criteria EC are as follows:
- EC1 Full text not accessible.
- EC2 It is not in the English language.
- EC3 It is not a scientific article published in Annals of events or journals.
- EC4 It is not about deep learning applied to PCXR.
- EC5 It was published before 2010.
- EC6 It is not a primary study.
- EC7 It is an old version of a study already considered.

The exclusion of a study occurs when it falls into at least one of such exclusion criteria. If not excluded, the study must meet each of the following inclusion criteria: IC:
- IC1 It is a primary study.
- IC2 It is about deep learning applied to PCXR.
- IC3 It was published after 2010.

B. Conducting

The conduction phase encompasses the activities of identification and selection of primary studies, data extraction and synthesis. The search strategy as part of the study protocol allows the identification of the studies, whereas the selection of these relies on inclusion and exclusion criteria and assessment quality criteria for primary studies, both previously defined in the study protocol. The data extraction activity starts as soon as the relevant primary studies are selected. Next, a synthesis of these studies is performed to answer the research questions of the SM.

To decide when studies should be rejected or not, we read the title, summary, and keywords of each study, and if they were not sufficient for decision making, read the full article. After applying the inclusion and exclusion criteria of 178 studies identified in the automatic search, we had 78 duplicate articles, 74 removed by EC and 26 included. The Table III

| DIGITAL LIBRARY | QUERY |
|-----------------|-------|
| ACM DL          | (Title:(((deep OR neural OR convolution) AND (network OR learning)) OR CNN) AND Title:(((chest OR lung OR thorax) AND (x-ray OR radiography) OR cxr) AND Title:pediatric OR infant OR baby OR newborn OR child OR paediatric)) OR (Abstract:(((deep OR neural OR convolution) AND (network OR learning)) OR CNN) AND Abstract:(((chest OR lung OR thorax) AND (x-ray OR radiography) OR cxr) AND Abstract:pediatric OR infant OR baby OR newborn OR child OR paediatric)) OR (Keyword:(((deep OR neural OR convolution) AND (network OR learning)) OR CNN) AND Keyword:(((chest OR lung OR thorax) AND (x-ray OR radiography) OR cxr) AND Keyword:pediatric OR infant OR baby OR newborn OR child OR paediatric)) |
| Guide to Computing Literature | (deep OR neural OR convolution) AND (network OR learning) OR CNN AND (((chest OR lung OR thorax) AND (x-ray OR radiography) OR cxr) AND Abstract:pediatric OR infant OR baby OR newborn OR child OR paediatric) |
| Engineering Village | (deep OR neural OR convolution) AND (network OR learning) OR CNN AND (((chest OR lung OR thorax) AND (x-ray OR radiography) OR cxr) AND Abstract:pediatric OR infant OR baby OR newborn OR child OR paediatric) |
| Embase | (deep OR neural OR convolution) AND (network OR learning) OR CNN AND (((chest OR lung OR thorax) AND (x-ray OR radiography) OR cxr) AND Abstract:pediatric OR infant OR baby OR newborn OR child OR paediatric) |
| IEEE Xplorer | (deep OR neural OR convolution) AND (network OR learning) OR CNN AND (((chest OR lung OR thorax) AND (x-ray OR radiography) OR cxr) AND Abstract:pediatric OR infant OR baby OR newborn OR child OR paediatric) |
| Scopus | TITLE-ABS-KEY (((deep OR neural OR convolution) AND (network OR learning)) OR CNN) AND (((chest OR lung OR thorax) AND (x-ray OR radiography) OR cxr) AND Abstract:pediatric OR infant OR baby OR newborn OR child OR paediatric) |
| PubMed | (((deep OR neural OR convolution) AND (network OR learning)) OR CNN) AND (((chest OR lung OR thorax) AND (x-ray OR radiography) OR cxr) AND Abstract:pediatric OR infant OR baby OR newborn OR child OR paediatric) |
| | OR (pediatric OR infant OR baby OR newborn OR child OR paediatric) |
TABLE III: Result of inclusion and exclusion criteria applied

| DIGITAL LIBRARY    | Identified | Duplicated | Removed | Included |
|--------------------|------------|------------|---------|----------|
| ACM DL             | 6          | 5          | 1       | 0        |
| Engineering Village| 36         | 33         | 3       | 0        |
| Embase             | 32         | 17         | 15      | 0        |
| IEEE Xplorer       | 13         | 7          | 4       | 2        |
| PubMed             | 16         | 16         | 0       | 0        |
| Scopus             | 75         | 0          | 51      | 24       |
| TOTAL              | 178        | 78         | 74      | 26       |

shows the result of this process for each digital library.

In the Table IV a breakdown of the exclusion criteria in each base. Importantly, criterion 4 was responsible for the largest number of excluded articles, followed by criterion 5, and criteria 2 and 7 were the least responsible. This is because, in most systematic studies, small rates of return often occur for studies relevant to the research topic studied [36], [42]. Compared to criteria 2 and 7, it is agreed that most publications are in the English language and unique versions.

TABLE IV: Breakdown of the exclusion criteria

| EXCLUSION CRITERIA | EC1 | EC2 | EC3 | EC4 | EC5 | EC6 | EC7 | TOTAL |
|--------------------|-----|-----|-----|-----|-----|-----|-----|-------|
| ACM DL             | 0   | 0   | 0   | 1   | 0   | 0   | 0   | 1     |
| Engineering Village| 1   | 1   | 0   | 0   | 1   | 0   | 0   | 3     |
| Embase             | 1   | 0   | 4   | 10  | 0   | 0   | 14  | 14    |
| IEEE Xplorer       | 0   | 0   | 0   | 3   | 1   | 0   | 0   | 4     |
| PubMed             | 0   | 0   | 0   | 0   | 0   | 0   | 0   | 0     |
| Scopus             | 5   | 1   | 0   | 26  | 10  | 8   | 1   | 51    |
| TOTAL              | 7   | 2   | 4   | 40  | 12  | 8   | 1   | 74    |

In addition to these steps, we also performed the snowball technique in three from 26 selected studies. The most cited and correlated among the selected studies (see Table V). This technique gave us the advantage of the evaluation of our search string by comparing the returned articles with those referenced by these studies. A relationship with these three studies follows.

* S3: A transfer learning method with deep residual network for pediatric pneumonia diagnosis [43].
* S10: Classification of images of childhood pneumonia using convolutional neural networks [44].
* S18: Identifying Medical diagnoses and Treatable Diseases by Image-Based Deep Learning [45].

TABLE V: Correlation between selected studies

| Study | Cited by |
|-------|----------|
| S3    | [S2, S16]|         |
| S4    | [S16]    |         |
| S10   | [S11, S15]|        |
| S14   | [S2]     |         |
| S18   | [S2, S3, S5, S6, S11, S12, S13, S16, S18, S23, S24, S25] | |
| S24   | [S25]    |         |
| S26   | [S9]     |         |

Regarding duplicate studies, only to example the Table VI lists the select papers and its duplicates per information source. The ◦ symbol represents each study instance excluded because of its copies in more than one bibliographic database. The ⋆ symbol, in turn, represents the instance of a duplicate study kept for the extraction phase. Therefore, of the 26 studies selected after exclusion criteria only 6 of them do not have duplicates (S2, S4, S11, S16, S22, S23).

The number of papers identified, duplicated, excluded and evaluated before data extraction and mapping process is found in Figure 4 whereas the list of 26 studies selected after this process, which included the technique of snowballing, can be seen in the Table VII.

IV. DATA EXTRACTION AND MAPPING PROCESS

This section describes the most important aspects and information extracted from the full-text reading of the ten primary studies selected, which includes:

- the main objective and respective RQs;
- the selection methods of primary studies; and
- the evidence collected from the synthesis of these studies.
### TABLE VI: Select papers and its duplicates per information source

| Study          | S1  | S2  | S3  | S4  | S5  | S6  | S7  | S8  | S9  | S10 | S11 | S12 | S13 | S14 | S15 | S16 | S17 | S18 | S19 | S20 | S21 | S22 | S23 | S24 | S25 | S26 |
|----------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| ACM DL         | ◦   | ◦   |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| Engineering Village | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   |
| Embase         | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   |
| IEEE Xplorer   | •   | ◦   |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |     |
| PubMed         | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   | ◦   |
| Scopus         | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   | •   |

### TABLE VII: Selected primary studies

| ID  | TITLE                                                                 | Reference |
|-----|----------------------------------------------------------------------|-----------|
| S1  | A Generic Approach to Lung Field Segmentation from Chest Radiographs using Deep Space and Shape Learning | [25]      |
| S2  | A novel transfer learning based approach for pneumonia detection in chest X-ray images | [46]      |
| S3  | A transfer learning method with deep residual network for pediatric pneumonia diagnosis | [43]      |
| S4  | An Efficient Deep Learning Approach to Pneumonia Classification in Healthcare | [47]      |
| S5  | Automated deep learning design for medical image classification by health-care professionals with no coding experience: a feasibility study | [48]      |
| S6  | Automated pneumonia diagnosis using a customized sequential convolutional neural network | [49]      |
| S7  | Automatic Catheter and Tube Detection in Pediatric X-ray Images Using a Scale-Recurrent Network and Synthetic Data | [50]      |
| S8  | Automatic tissue characterization of air trapping in chest radiographs using deep neural networks | [51]      |
| S9  | Classification of bacterial and viral childhood pneumonia using deep learning in chest radiography | [52]      |
| S10 | Classification of images of childhood pneumonia using convolutional neural networks | [41]      |
| S11 | Classification of pneumonia from X-ray images using siamese convolutional network | [53]      |
| S12 | Deep Learning Method for Automated Classification of Anteroposterior and Posteroanterior Chest Radiographs | [54]      |
| S13 | Deep learning to automate Brasfield chest radiographic scoring for cystic fibrosis | [55]      |

### TABLE VII: (continued)

| ID  | TITLE                                                                 | Reference |
|-----|----------------------------------------------------------------------|-----------|
| S14 | Deep learning, reusable and problem-based architectures for detection of consolidation on chest X-ray images | [56]      |
| S15 | Detecting pneumonia in chest radiographs using convolutional neural networks | [57]      |
| S16 | Detection of Pediatric Pneumonia from Chest X-Ray Images using CNN and Transfer Learning | [58]      |
| S17 | Discriminant Analysis Deep Neural Networks | [59]      |
| S18 | Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning | [45]      |
| S19 | Learning to Recognize Chest-Xray Images Faster and More Efficiently Based on Multi-Kernel Depthwise Convolution | [60]      |
| S20 | LungAIR: An automated technique to predict hospitalization due to LRTI using fused information | [61]      |
| S21 | Marginal shape deep learning: Applications to pediatric lung field segmentation | [62]      |
| S22 | Pulmonary rontgen classification to detect pneumonia disease using convolutional neural networks | [63]      |
| S23 | Simultaneous Lung Field Detection and Segmentation for Pediatric Chest Radiographs | [64]      |
| S24 | Two-stage deep learning architecture for pneumonia detection and its diagnosis in chest radiographs | [65]      |
| S25 | Using deep-learning techniques for pulmonary-thoracic segmentations and improvement of pneumonia diagnosis in pediatric chest radiographs | [66]      |
| S26 | Visualizing and explaining deep learning predictions for pneumonia detection in pediatric chest radiographs | [67]      |
### TABLE VIII: Summary of standard extraction form

| Study | FQ1 | FQ2 | FQ3 | FQ4 | FQ5 | FQ6 | FQ7 | FQ8 | FQ9 | FQ10 | FQ11 | FQ12 | FQ13 | FQ14 | FQ15 | FQ16 | FQ17 | FQ18 | FQ19 | FQ20 | FQ21 | FQ22 |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|------|------|------|------|------|------|------|------|------|
| S1    | 2019 | B   | A   | B   | A,D | C   | Y   | A,B | PA  | 568  | R    | Y    | B    | Y    | B    | N    | n/a  | Y    | D    | J,K  | A    | SEQ  |
| S2    | 2019 | B   | A   | B   | A   | C   | Y   | A,B | PA  | 5232 | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | A,G  | F    | B    | E    |
| S3    | 2020 | B   | A   | C   | Y   | C   | AP  | 5856 | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | B    | A    | B,F,G | E    | PAR  |
| S4    | 2020 | B   | A   | C   | Y   | C   | AP  | 5856 | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | A    | C,D  | B    | PAR  |
| S5    | 2019 | B   | B   | E   | C   | Y   | C   | AP  | 5827 | R    | Y    | A,F  | N    | n/a  | N    | n/a  | Y    | A,G  | B    | E    | SEQ  |
| S6    | 2019 | C   | A   | B   | C   | Y   | E   | D,E | AP  | 51   | R    | Y    | A,F  | Y    | A    | B    | N    | n/a  | N    | N    | A    | B    |
| S7    | 2018 | C   | A   | B   | C   | Y   | E   | F   | AP  | 51   | R    | Y    | A,F  | Y    | A    | B    | N    | n/a  | N    | N    | A    | B    |
| S8    | 2018 | C   | A   | B   | C   | Y   | E   | L,F | PA  | 10   | R    | Y    | F    | Y    | D    | N    | n/a  | N    | H    | K    | A    | X    |
| S9    | 2017 | B   | A   | B   | C   | N   | E   | N   | 314  | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | D    | I    | K    | A    | X    |
| S10   | 2018 | C   | A   | B   | C   | Y   | N   | E   | F   | 5232 | R    | Y    | A    | N    | n/a  | N    | n/a  | Y    | A    | B    | F    | K    |
| S11   | 2019 | C   | A   | B   | C   | Y   | C   | AP  | 5856 | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | A    | C,D,G | B    | X    |
| S12   | 2019 | B   | A   | B   | C   | Y   | D,E | F   | 5941 | R    | Y    | A    | Y    | B    | Y    | A    | A    | C    | E    | SEQ  |
| S13   | 2019 | C   | A   | B   | C   | Y   | C   | AP  | 5856 | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | A    | B    | E    | SEQ  |
| S14   | 2019 | B   | A   | B   | A   | C   | Y   | D   | PA  | 5232 | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | A    | G    | J    | E    |
| S15   | 2019 | B   | A   | B   | A   | C   | Y   | D   | PA  | 5232 | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | A    | G    | J    | E    |
| S16   | 2019 | B   | A   | B   | A   | C   | Y   | D   | PA  | 5232 | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | A    | G    | J    | E    |
| S17   | 2019 | C   | A   | B   | C   | Y   | C   | AP  | 5856 | R    | Y    | A    | N    | n/a  | N    | n/a  | Y    | A    | C    | E    | X    |
| S18   | 2018 | C   | A   | B   | C   | Y   | C   | AP  | 5856 | R    | Y    | A    | N    | n/a  | N    | n/a  | Y    | A,B  | A,F,K | B    | PAR  |
| S19   | 2020 | B   | A   | B   | C   | Y   | C   | D   | F   | 11807| R    | Y    | A    | N    | n/a  | N    | n/a  | B    | A    | C    | F,I,K | B    | PAR  |
| S20   | 2020 | C   | A   | B   | C   | N   | E   | N   | 314  | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | D    | I    | K    | A    | X    |
| S21   | 2020 | B   | A   | B   | A   | C   | Y   | N   | E   | 314  | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | D    | I    | K    | A    | X    |
| S22   | 2019 | C   | A   | B   | C   | N   | E   | F   | 5232 | R    | Y    | B    | N    | n/a  | N    | n/a  | Y    | A    | C    | F,I,K | B    | PAR  |
| S23   | 2019 | C   | A   | B   | C   | N   | E   | F   | 5856 | R    | Y    | A    | Y    | B    | N    | n/a  | Y    | A    | C    | F,I,K | B    | PAR  |
| S24   | 2019 | C   | A   | B   | C   | Y   | C   | AP  | 5856 | R    | Y    | A    | Y    | B    | R,D  | N    | n/a  | Y    | A    | C    | F,I,K | B    | PAR  |
| S25   | 2019 | A   | B   | B   | C   | Y   | C   | PA  | 5504 | R    | Y    | B,F  | Y    | B,C,F | N    | n/a  | Y    | A    | D    | F,J,K | E    | SEQ  |
| S26   | 2019 | C   | A   | B   | C   | Y   | C   | AP  | 5856 | R    | Y    | A,B  | Y    | A,B,D | N    | n/a  | N    | A    | G    | A,C,F,G,K | B    | PAR  |

**Legend:**
- **FQ1. Year of publication?** Year (YYYY)
- **FQ2. Publishing vehicle?** A) Magazine, B) Journal, C) Event
- **FQ3. Research type classification?** A) Solution proposal, B) Evaluation, C) Validation, D) Experience report, F) Opinion
- **FQ4. Research method adopted?** A) case study, B) controlled experiment, C) simulation, D) prototyping
- **FQ5. Type of Contribution?** A) Algorithm, B) Application, C) Framework, D) Product, E) Others
- **FQ6. Type of radiographic view used?** L) Lateral, AP) frontal Anterior-Posterior, PA) frontal Posterior-Anterior, F) frontal AP and PA, X) not available
- **FQ7. Did you use public dataset?** Y) yes, N) no
- **FQ8. Dataset used (PCXR)?** A) Belarus, B) CNHS, C) Guangzhou, D) NIH, E) Private
- **FQ9. Did you require authorization from an ethics committee?** Y) yes, N) no
- **FQ10. Amount of images used (only PCXR)?** Integer
- **FQ11. Origin of the images?** A) real, B) Synthetic
- **FQ12. Used any additional information?** Y) yes, N) no
- **FQ13. What additional information was used?** A) diagnostic labels, B) masks, C) other tests E) social information, F) Clinical report, G) Reference values
- **FQ14. Do you perform any preprocessing steps?** Y) yes, N) no
- **FQ15. What preprocessing step are used?** A) Normalization, B) Resizing, C) Cropping, D) Segmentation, E) Suppression F) Improvement
- **FQ16. Does it make use of any international standards?** Y) yes, N) no
- **FQ17. What international standard are used?** A) HIPAA (Health Insurance Portability and Accountability Act) B) HL7, C) HITECH , D) ISO, E) IEC
- **FQ18. What evaluation metrics are used?** A) Recall, B) Precision, C) Accuracy, D) Loss, E) Confusion Matrix, F) AUC, G) F1 Score, H) Errors, I) Speed, J) Dice coefficient, K) Others
- **FQ19. What deep learning architecture is used?** A) Autoencoder, B) CNN, C) LSTM, D) Recurrent Neural Network, E) Residual Neural Network, F) Restricted Boltzmann Machines, X) not reported
- **FQ20. Processing approach?** SEQ) sequential, PAR) parallel / GPU, X) not reported
- **FQ21. What is the task covered?** A) Classification, B) Diagnostic, C) Enhancement, D) Segmentation, E) Object recognition, F) Localization, G) Detection, H) Prediction / Prognostic
- **FQ22. Non-applicable**
In this extraction phase, two independent reviewers extracted the data using a standardized form, while a third, more experienced reviewer was left to resolve doubts and disagreements. An important note is that some of the features may appear in several studies; therefore, the totals may not always correspond to 100%.

The extraction standard form can be seen summarised in the Table VIII. The questions (FQ[i-th]) in this form are intended to cover the entire research topic. Some of them, like FQ2, FQ3, FQ4, are based on the classifications brought by [37], while FQ21 on the scheme of DL architectures classification proposed by [68].

In Table IX the relationship between the research questions (RQs) and the extraction form questions (FQs), the latter used to answer the former. The analysis of each of the research questions follows.

All primary studies selected for data extraction and synthesis date from the last five years, according to the criteria adopted in their selection, and were returned only from three of the six digital libraries, 24 from Scopus, 2 from IEEE Xplorer, in automatic search.

A. About the Research Questions (RQs)

The answers shown next, in each RQ, represent the synthesis of the results obtained in the extraction by FQs, and far from being conclusive answers, they are much more of a strong indication of the possible paths taken in the research topic under analysis.

RQ1: What is the state of the art of DL on PCXR images tasks? Although the answer to this main question cannot be given by a single question FQ from our extraction form or one of the subsequent RQs (detailed in the sequence of this text), it can be understood in the aggregate of these questions.

For example, from the extraction performed in the 26 studies, all back date 2016, it is clear that this research topic is still of great interest to the scientific community, and this interest lies in a growth curve, the what it is corroborated by time graphs of Figure 5 built from 26 studies of our driving phase, and that of Figure 1 automatically generated by the Google Trends tool under the terms "deep learning" and "chest x-ray" and already shown at the beginning of this work.

The publications are equally divided between journals and events and most are classified as proposed solutions, adopting controlled experiments as a research method (FQ2, FQ3 and FQ4). This evidence added to the results presented in these studies allows us to see a constant process of evolution, with new limits being established every day, and a search for efficiency, effectiveness and safety that allow its adoption in the hospital and health care environments.

The techniques applied to the studies lead us to know the architectures of the Convolutional Neural Network (CNN) and the Residual Neural Network (ResNet) (F21) as the main actors in image processing applications with a history of high precision and accuracy.

The extraction standard form can be seen summarised in the Table VIII. The questions (FQ[i-th]) in this form are intended to cover the entire research topic. Some of them, like FQ2, FQ3, FQ4, are based on the classifications brought by [37], while FQ21 on the scheme of DL architectures classification proposed by [68].

In relation the tasks about PCXR images, some seem to attract more attention from the scientific community, such as classification and detection (FQ19), but others have also been researched, which is a good indication of their importance in this research field. In addition, the small number of public PCXR data sets has been an additional challenge, currently circumvented with learning transfer and data augmentation techniques, but not yet explored using Adverse Network architectures (taking our 26 articles).

Whereas DL has shown impressive advances in many fields, in the medical field and more specifically CXR imaging this technique is still in its infancy. Many limitations are yet to be overcome, such as better readability of models that allow the confrontation with the opinion of medical specialists, the establishment of international standards and specific metrics to guide and validate the results of the studies and the transition of these proposal solutions, that still are in the field of research to the application in industry, commerce, and hospital environments.

In conclusion, and already noted by [18] and [27] DL, it is an excellent and powerful and ever-expanding technique, which can, for example, combine image analysis and radiology text reports analysis, which brings incredible possibilities and makes us believe that very soon may come reality CAD systems that generate automated reports for CXR images.

RQ2: Which tasks applied to chest radiographs imaging are most addressed by deep learning techniques? As noted in Figure 6 virtually all tasks were covered in the analyzed studies, except for object enhancement and recognition tasks. Although the analysis is supported by only 26 studies, it can be observed that research has a wide range of tasks, with the exception of the task of classification with greater attention and prediction/prognostic with lesser other tasks has received similar attention.

RQ3: What are the metrics used for assessment? It may be premature to indicate which metrics are best for each task associated with PCXR images based on 26 studies alone, but it is clear that for classification, metrics such as F20-C and F20-F have been more adopted, whereas in segmentation the F20-K metric has been used most often. These metrics are already well known in the literature, which reveals that studies in DL and PCXR are not concerned with the development of
TABLE IX: A summary of the relationship between research questions and form questions.

| X | RQ1 | RQ2 | RQ3 | RQ4 | RQ5 | RQ6 | RQ7 | RQ8 | RQ9 | RQ10 | RQ11 | RQ12 |
|---|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|
| FQ1 | ◦   |     |     |     |     |     |     |     |     |      |      |      |
| FQ2 | ◦   |     |     |     |     |     |     |     |     |      |      |      |
| FQ3 | ◦   |     |     |     |     |     |     |     |     |      |      |      |
| FQ4 | ◦   |     |     |     |     |     |     |     |     |      |      |      |
| FQ5 | ◦   |     |     |     |     |     |     |     |     |      |      |      |
| FQ6 | ◦   |     |     |     |     |     |     |     |     |      |      |      |
| FQ7 | ◦   |     |     |     |     |     |     |     |     |      |      |      |
| FQ8 | ◦   |     |     |     |     |     |     |     |     |      |      |      |
| FQ9 | ◦   |     |     |     |     |     |     |     |     |      |      |      |
| FQ10 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ11 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ12 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ13 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ14 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ15 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ16 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ17 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ18 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ19 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ20 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ21 | ◦  |     |     |     |     |     |     |     |     |      |      |      |
| FQ22 | ◦  |     |     |     |     |     |     |     |     |      |      |      |

Legend:  
RQ. Research Question ◦ It indirectly answers the research question.  
FQ. Form question ● It directly answers the research question

Same CXR has been one of the most widely performed diagnostic tests in the world and there is an abundant number of real images (FQ11), this is not reflected in the number of pediatric image data sets available. Difficulties are encountered, among other things, in the privacy and security restrictions of patient records and in the arduous and expensive task of validating diagnoses and labeling (mainly associated with detection and segmentation).

In the related 26 papers of this work the largest set was being provided from Guangzhou Women and Children’s Medical Center (FQ8-C) with 5856 images which is consequently the most cited. Other public sets have also been used in the studies, as less frequently, such as CNHS data set (FQ8-B) collected at Children’s National Health System or the subset of pediatric images from NIH Clinical Center data set (FQ8-D).

The studies S1, S21, S23 for example that present a small number of images are related specifically to the segmentation task, explained by the difficulty of creating these types of data sets, as they require a lot of time, experience and care to correctly define the masks that will be used as a reference. Moreover, another observation about these studies is that, despite presenting good results in the evaluated metrics, they bring the worst comparative evaluations in relation to other studies in the literature, a fact that, linked to the reduced number of images, ends up putting their results in suspicion. On the other hand, the studies that present the largest number of new evaluation metrics and are quite comfortable with their use.

**RQ4:** What are the main data sets used in this research field and how are they organized? Although Figure 7 FQ7 and FQ10 show that most studies use public sets with a much larger number of images than the private sets mentioned, they are still few and with a limited number of images, even more, if we compare it to public sets from other domains that have hundreds of thousands of images like the ImageNet and COCO [69] data sets, or from sets from the same domain, like the Chest X-ray14 [70] from NIH Clinical Center and PadChest [71] from Hospital San Juan de Alicante.
of images are also those that bring stronger results and evidence of their contribution, mainly because they make a more detailed comparative evaluation with other studies in the literature.

We can see also in Figure 7 and responses from FQ9 the frontal view (AP/PA) is predominant with most in projection AP while the lateral view was used two studies only (although one study the projection-type was not available).

This is explained by the fact that this projection allows a better evaluation, leaving scapula out of the visual field and the size of heart closest to the actual size also projection is preferred because it is a standard radiographic technique this allows accurate and valid comparison between repeated AP/PA CXRs (72).

Finally, although the number of images cannot be said to be the determining factor in the quality of the study or in the applied DL technique, mainly because, as shown in [73], the gain related to the increase in the number of images the images have limitations, this observation can support the generalization of the proposed solution and its application in more cases, reducing overfitting.

**RQ5: Did the work have ethics committee authorization?**

One important aspect of medical area research is the fact what it is around restrictions as high-security information, requires the anonymity of patients and authorization to use of data. It is, however, important and indeed a requirement of most health journals, that authors of all investigations on human participants state whether the study was approved by an ethics committee and how consent was obtained (74).

We did not find information on authorization from any ethics committee in 11 of the 26 studies analyzed (FQ18) and, although this is not enough to state that they did not have one, it may indicate that the demands in this direction do not receive as much attention; on the other hand, it is important to note that only two of these 11 studies (S20, S23) did not use public data sets (FQ7).

Points out that most public data, especially that of government agencies or government-sponsored research, is collected under protocols approved by one or more ethics committees and therefore additional approval is not required, especially when there is no any identification of individuals in that data and since that data is already available to the public. We can, therefore, believe that most research is supported by some institutional review boards, whether in data collection or secondary analysis.

**RQ6: What are the neural network architectures used in the works?**

Currently, deep learning is the dominant technology in our daily lives, having an impact in several areas, ranging from entertainment, business, security to health. This technology, made up of neural networks, uses several (deep) layers of units with highly optimized algorithms and architectures. Deep learning has a large number of architectural models, which can be differentiated by the number of layers, type of network, method or training algorithm, among others.

The choice and adoption of a neural network architecture, however, it must consider another more important aspect, its application domain. Long Term Memory (LSTM), for example, are commonly applied in the understanding and translation of natural language, gesture recognition and writing; Autoencoders to reduce dimensionality, adverse networks in resource learning and topic modeling, Residual Networks (ResNet) and Convolutional Neural Networks (CNN) for image recognition, just to name a few.

Thus, it is expected that the adoption of an architecture considers its application domain, to taking advantage of its characteristics and obtain better results. Therefore, in our primary studies selected and under analysis, CNNs and ResNets and their variations are prevalent (FQ21-B and FQ21-E) and the reasons for this seem obvious, as these architectures have an excellent record of accuracy and precision, are experts in recognizing and classifying images, are available for free and in different programming languages, and in addition, are the ones that have more applications related to the studies of this research.

On the other hand, open questions from these studies point to more architectures that could be used, for unsupervised training, such as Autoencoders and RBM networks, to generate realistic false data like Adverse Generating Networks (GANs), in order to overcome the limitation of data for training and also with LSTM networks for generating reports in order to provide greater clarity and intelligibility to the results, for example.

**RQ7: When and in which vehicle type was the articles published?** As mentioned in the introduction to this article, and later in the Section, all selected studies start from 2016 with the majority of 2019 and 2020 (see Figure 5 and FQ1) which strengthens the discourse of the growing interest of the matter addressed in this research agenda.

These studies are distributed mainly into two types of publications: events such as conferences and symposiums, and journals that are the majority these publications, only a few in magazines (FQ2).

Journals are usually related to original research that has gone through a rigorous process with many rounds of peer expert review in the field. Event articles have a faster and less rigorous review process and favor interaction with inter-
national audiences working in the same field, with negotiations and feedbacks being common. Magazines can bring opinions from authors and may not necessarily be supported by scientific literature, although they should not be overlooked in systematic studies.

Articles from journals and events are most commonly chosen and considered as the best sources of citation and, in addition, provide more directions for future research, so the publications in this research agenda point strongly to this path.

RQ8: What details of types of data and process applied on DL technique? As mentioned in RQ1 and RQ6, CNNs and ResNets were the predominant architectures in the studies, being applied mainly to the classification and detection tasks and with pneumonia as the main pathology addressed, and for reasons already mentioned in the introduction to this article. Therefore, considering only these main architectures, all studies used supervised training as a learning technique with the application of backpropagation and gradient descent based algorithms, typical features of these architectures [68].

An important observation is that the (FQ22-SEQ) sequential processing approach was mentioned in only four of all studies, which proves that parallel processing approaches are becoming a standard approach, mainly due to advances in graphics processing units (GPU) and its processing power. However, even with these advances in processing, most studies did not fail to use preprocessing steps, as we can see in Figure [5] among which the most used ones have been the normalization (FQ15-A) and resizing (FQ15-B). This is quite in reason of the benefits they can bring, as to train networks is a costly task, and steps that reduce this work are always appreciated.

RQ9: Which type of contribution results? As we can see in Figure [9] and answers in (FQ-5), the vast majority of studies presented some framework or algorithm as a proposal or contribution of their work, mainly related the application and adaptation of CNN and ResNet architectures, to some cases, a combination of models of these architectures. In relation to the other studies, both are evaluation studies, S5 is an evaluation of the use of DL automated software by health professionals with no coding experience or DL and S13 that evaluates the hypothesis of a CNN deep model automate Brasfield score on CXRs of patients with cystic fibrosis (CF) with performance similar to that of a pediatric radiologist.

In view of what was presented, we can reach some conclusions: A) there is a great interest on the part of researchers to use, improve and develop deep learning models, B) the works are unanimous in pointing out the data limitation systematically, rigorously and carefully prepared for ensuring the generalization of the results to external data and different from those used in the construction of the models and C) although the research shows excellent performance in the use of these models, none of them brought a product or application as a result, which can be interpreted as research still in the stage experimental.

RQ10: Is there any international standard and is it applied? Today, the need for multi-system connectivity and electronic data transfer is growing in the Health Care sector. The necessity for integration of systems and for communication of information in this sector becomes evident when studying the variety of interested parties, the multitude of application their importance. A way to reach this is towards standardization one-time several requirements are evident through the fact that many experiments from a lot of different fonts [76].

In image archiving and communication systems (PACS), for example, it is common to use the international standard DICOM® (Digital Imaging and Communications in Medicine) [77], which among other issues defines rules for the transmission, storage and display of image information to ensure interoperability and integration between devices.

In this research agenda, we look for similar patterns, although the focus of the studies analyzed is not the generation of images, but the subsequent manipulation of them. Therefore, we consider that standards such as DICOM® should already be established, remembering that 85% of the studies used a public data set (FQ7) and that only 6 of the 26 studies have mentioned this pattern in their text.

Despite this importance, of the analyzed studies, only the studies S12 and S13 cited the use of some standardization. The lack of standardization must be explained by the lack of standards in that area or even by the fact that the studies are still in the academic environment. We believe that when the following solutions are applied to viable and industry application products, they may be appropriate for some standardization.
RQ11: How is the study classified? Based on Petersen et al. [28] and Wieringa et al. [78], the classification that best defines the type of research of the analyzed studies (88.5% of them) is the “Solution Proposal” (FQ3). This classification occurs because these studies propose new techniques or enhancements to existing techniques for solving tasks related to PCXR images (see FQ19). The authors of these studies also discuss their proposals and compare them with other related studies.

RQ12: Which the research method adopted? With respect to the adopted method [28], [78], with the exception of S14, which is also a “Case Study”, all others are “Controlled Experiments”, since they are performed in an academic environment under specific conditions, using a well-defined data set that does not it is affected by external factors.

V. RESEARCH AGENDA

In this research agenda, we carefully analyzed 26 studies [S1-S6] and found some evidence of gaps still present in the effective application of DL in pediatric x-ray radiological images and in the state of the art of these DL techniques. The existing solutions found in the research, although showing promising results, are still in the maturation stage, with responses that are still fragile to the requirements necessary for their clinical application. As a contribution, we have outlined a preliminary, but well-founded, research agenda to close this gap, containing studies that:

1) establish objective metrics for each task that helps researchers measure the performance and generalization of their solutions, as proposed by the American College of Radiology or even, that allow calculating the uncertainty estimates of the networks and their confidence level by physicians [79];

2) establish a set of standards for the creation and sharing of databases that are, for example, similar to the concept of ATM network or to the gold standard diagnosis and that guarantee security and anonymity, none of the analyzed studies explicitly mentioned this gap;

3) assess the impacts of generating data annotations via crowd-sourcing, especially for those whose process requires a high level of expertise, brings fatigue and is slow, scarce and very expensive;

4) evaluate the possible impact of reduced dimensionality on the accuracy of the models, although the absolute majority of the 26 studies analyzed perform this, no observation other than the processing cost is mentioned in this regard.

5) investigate architectures DL based on more than just data, for example, models based on a combination of data and physics [80], which can help with both generalization and interpretability issues.

6) Demonstrate the robustness/fragility of DL architectures applied to PCXR against adversary attacks or the presence of external noise;

7) investigate the application of DL in the task of generation, registering or retrieval pediatric chest X-ray images, those tasks were not even mentioned in the analyzed studies;

8) evaluate unsupervised DL models, such as variational auto-encoders (VAEs) and generative adversary networks (GANs), mainly to deal with unbalanced sets between classes, scarce in number or with unlabeled data;

9) demonstrate possible gain or not in the use of specific training as opposed to transference learning, still a big challenge in PCXR due to the limited number of data set with annotated images.

Finally, this agenda goes beyond the simple quantitative investigation of deep learning techniques applied to PCXR. It focuses on questions whose answers may have important implications for adopting or not adopting deep learning standards, strategies and architectures, as well as for lifting their limitations and pointing out their opportunities.

VI. DISCUSSION

Given the main research question RQ1 of this SM, which is the state of the art of DL solutions applied to PCXR images, 26 articles carefully selected by a rigorous protocol were subjected to a thorough analysis and synthesis guided by an extensive form of extraction. In order to answer this question, our SM also draws lines for a research agenda and tries unpretentiously to answer a provocative question about the maturity of DL in its application to pediatric chest images.

In a systematic way, our extraction and synthesis process reaches evidence that confirms several conclusions brought by secondary studies on this topic. The evidence recovered by the RQs and also observed in related studies, such as those described in Section [1] clearly indicate several gaps, challenges and, trends still present in this research topic. We leave here, therefore, the impression of what we believe to be the most latent points in this field of research.

First, although there are numerous metrics for assessment and measurement, there is as far as we know of no international reference manual or standard for measuring and evaluating deep learning tasks, especially those associated with pediatric chest X-ray images. A trend may be the adoption of assessment standards such as those applied to major public challenges as the by Kaggle or initiatives like that of the American College of Radiology (ACR) through algorithm review processes [26].

Second, applications in clinical medicine are not presented in any study analyzed, even in those with expressive results, while only one case study (S14) is reported, or that information has been suppressed by the studies or to a greater extent this it can indicate that the solutions are not sufficiently mature and safe.

Third, DL has been showing impressive results in several fields of research, surpassing, in some cases, human performance, as in precision agriculture, in autonomous vehicles and in the games industry in greater quantity and in the field of the medical image in less quantity, as in optical coherence tomography (OCT) for diabetic retinopathy detection. Regarding its
application in PCXR images, the results still seem incipient and with less impact, in our point of view needing more tests, which guarantee greater generalization and robustness of its solutions.

Fourth, our SM is not a list of all the open questions about the application of DL in pediatric chest X-ray images, and as already pointed out in Section V, many directions can still be followed. Therefore, our discussion only tries to bring out the most latent aspects presented in the 26 studies analyzed and which may be of some interest to future researchers.

Finally, our question about the maturity of the application of DL in pediatrics CXR images is provocative and, therefore, we do not intend here to give a definitive answer, just to raise some questions that can help the reader to take his experiments.

Why is it believed that the DL is still in childhood in pediatric chest X-ray images, because, although the DL was already applied to the analysis of medical images in 1995 by Lo et al. [81], only from 2015 did it have a massive application in medical images [18] and more precisely in 2016 in PCXR images [88], therefore, if we consider only this last information, we could chronologically define DL as a 4-year-old child. Similar observation to that of LeCun et al. [83] which states that systems that combine DL and reinforced learning are still in their childhood although they outperform passive vision systems in classification tasks.

Another evidence is the comparison of the application of DL in other areas, such as games and autonomous vehicles or the same for other medical images, such as optical coherence tomography (OCT) for the detection of diabetic retinopathy (S18), CT for cancer detection, evaluation skeletal bone age in X-ray images of the hand or automatic identification of evidence of classification in MRI of the spine that appears much more mature, just to name a few.

As already seen in this article (FQ6), another point that may explain the maturity stage of DL applications in CXR pediatrics is the fact that it is supported by supervised learning, dependent on a large amount of data and participation of professionals in an expensive and degraded data labeling process. The fact that research has not yet had any field of controlled experiments (FQ4) and clinical products or applications is not yet presented, with the result partially explained by the fragility of its generalizations and the need to standardize metrics most used by the test. performance and precision, in addition to the clear greater urgency in interpretability, simplicity and mathematical foundations or even uncertainty about their decisions, which enable the debate with doctors and that ethical questions about responsibility in these matters.

However, we cannot fail to highlight that the application of DL in pediatrics CXR images has surpassed the state of the art in several tasks and has made it possible to achieve quite impressive results, equivalent or superior in some cases to those achieved by medical specialists and that until then no technique knowingly mature had achieved.

Other points also pointed to the maturation of the application of DL in PCXR images, mainly those that refer to tools to support professional doctors, such as those related to the screening of suspected cases, suppression of bone structures, pre-processing processes for archiving and storage improvement, orientation correction or CXR vision rating.

Although some DL architectures such as CNN and ResNet seem to have more PCXR images, and tasks such as classification, detection, and segmentation have received more attention, this field of research is on the rise and has a lot of attention by the scientific community or leading to a belief that it is just a matter of time for other DL solutions will also be applied to PCXR images and other tasks. Our bet is that, soon, we will see annotation and report generation tools, strong use of unsupervised learning, and crowdsourcing to deal with data scarcity of labeled data about the unbalanced between classes and work in images with high resolution and dimension.

VII. Conclusions

Deep learning is not a new topic, seen for the first time more than three decades ago, about chest radiographs and their study with applied computational techniques, the same can be said [18]. Hundreds of works, as shown in Figure 4, have been published combining these subjects, including several secondary studies [34], [83], [33], [18], [36] that provide photographs at different times in the evolution of these topics. To the best of the authors’ knowledge, however, no SM study has been carried out in research related to the development of deep learning techniques applied to pediatric or non-chest X-ray images. Therefore, a mapping that brings a deep immersion of the details and characteristics of these techniques applied to PCXR images and that still proposes a research agenda to meet the gaps and trends of this topic, can add some value to new researchers.

A consolidated of 26 primary studies from 178 selected studies is presented with a systematic and complete analysis of a hot topic and of growing interest, while the lack of a similar study, as far as we know, justifies the design of this unprecedented research agenda.

The detailed protocol presented in Section III allows other researchers to validate, reproduce and extend this study, thus constituting a significant contribution to this study.

We understand that this study, finding only 26 articles, points to an area that is still evolving, which in fact has taken important steps, but that still needs to present more studies to reach greater maturity. In this sense, we believe that it can be said that the application of DL on PCXR is still in childhood and we are confident that this research agenda has contributed to its growth and maturity.

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