Deep Learning for Chest-x-ray analysis: a Systematic literature review

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Abstract:

Recent advances in deep learning have yielded promising performance in many medical image analysis tasks. As the most commonly performed radiological examination in 2021, chest X-ray is a particularly important modality with a variety of uses under consideration. In recent years, the publication of several large publicly available chest radiograph datasets has increased research interest and the number of publications. In this paper, we review all studies using Deep His Learning on chest radiographs and classify the work by task.

Image-level prediction (classification and regression), segmentation, localization, and image generation Customization of Mer domain. Commercial applications are described in detail and a comprehensive discussion of the current state of the art and possible future directions is provided.

Keywords:

Deep learning, chest radiography, chest X-ray analysis.

1. Introduction:

The chest radiograph, or CXR, has been the mainstay of radiological imaging for decades and is still used the most frequently. The most common industrial radiological inspection around the world The average number of erect breasts reported by developed nations is 238 X-arXiv: 2103.08700v1 (AP) At the X-ray source, both perspectives are regarded as frontal radiographic images per 1000 people annually (United Nations, 2008). Only in the United States were 129 million CXR Images reportedly captured in 2006. (Mettler et al.,2009). Demand and supply for CXR images might change depending on how affordable and low-radiation they are, as well as how sensitive they are to different medical conditions. CXR is often the first imaging exam acquired Remain central to screening, diagnosis and management Widespread disease. Chest radiographs mainly can be divided into three types. depending on patient position and orientation relative to

X-ray source and detector panel:

backwards, in front of, and sideways. Anteroposterior (AP) and posterior anterior (PA) positioned in front of or behind the patient. The patient is often lying supine when AP pictures are collected. Typically, patients are upright during PA recording.

Get Landscape pictures are frequently employed with Project an X-ray picture of her from one side together with the PA picture. Usually from right to left, patient to patient. a case of Figure 1 displays these image types. Because of the superposition of the anatomy along the projection path, interpreting chest x-rays can be challenging. Due of this consequence, it may be exceedingly challenging. Find anomalies in specified places (e.g. knots) Small or sub-resolution images (Quekel et al., 2001; Balabanova et al., 2005; Young, behind the frontal CXR) Examine anomalies or correctly identify various anomalies An abnormal pattern. Radiologists typically have considerable inter-observer variability (Analysis of CXR 1994 reveals this).

amount and complexity of CXR images recorded The importance of interpretation in therapeutic practise has long been recognised. Researchers have been motivated to create automated CXR analysis techniques. yes. In fact, since then, this has been a topic of study.The first publications describing automated anomalies were published in the 1960s. Potential revenue from automated CXR analysis for City Detection System includes sub Findings, prioritisation of time-sensitive cases, automation, and analytics on tedious everyday duties and circumstances where radiologists are not present (e.g. in developing countries).

It offers a choice for image analysis tasks and has significantly influenced the field of medical imaging. The CXR research community has profited recently from the publication of multiple large-scale labelled databases, which were largely made possible by automated processing of radiation reports to generate labels. Deep learning is famously data-hungry. I have gotten With the publication of 112,000 pictures of him from the NIH Clinical Center in 2017, this trend got underway (Wang et al., 2017b). His three tagged databases—CheXpert (Irvin et al., 2019), MIMIC-CXR (Johnson et al., 2019), and PadChest (Bustos et al., 2020)—collected more than 755,000 pictures just in 2019 alone. released in In this paper, we demonstrate the effect of making these data publicly available on the quantity of deep learning articles in this field. Previous studies on deep learning or computer-assisted diagnosis have been done on medical image analysis (Litjens et al., 2017; van Gin-neken, 2017; Sahiner et al., 2018; Feng et al., 2019). To CXR (Qin et al., 2018; Kallianos et al., 2019; Anis et al., 2020). Recent analyses of deep learning in chest radiography have not been extensive in terms of the literature and methodology that have been examined, the description of the public datasets that are accessible, or the assessment of potential future developments and trends in this area.

The literature review for this paper contains 42 articles published between 2015 and 2022, categorized by application. A comprehensive list of public records is also provided, including the number and type of images and captions, as well as some discussion and caveats regarding various aspects of those records. Trends and gaps in the field are described, important contributions are discussed, and possible future research directions are identified. It also discusses commercial software available for chest x-ray analysis and how best to translate research findings into the clinic.

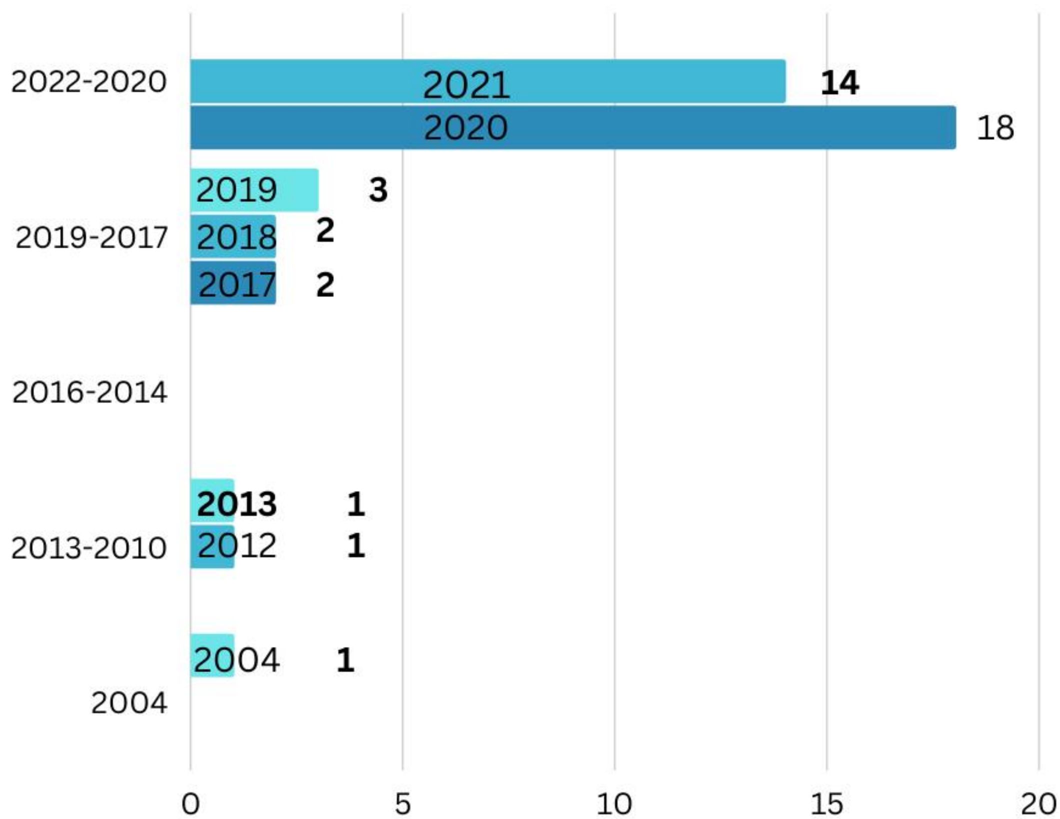

Fig 1: Number of publications collected with respect to year

The initial selection of literature to be included in this review was obtained as follows: A selection of papers was created us-ing a PubMed search for papers with the following query.

chest and ("x-ray" or xray or radiograph) and ("deep learning" or cnn or "convolutional" or "neural network")

2 Research Method:

We framed the questions with **SPIDER** (Sample, Phenomenon of Interest, Design, Evaluation, Research type)

2.1 Research paper picking:

RP1: Does the paper provide a clear description of the method used to analyze the chest X-rays and the deep learning model employed?

This helps pick the research papers which provides the best clarification to its title and its method which is pre-defined, and also the papers with high quality have the ability to be selcted under this category.

RP2: Are the results of the study statically significant and do they support the conclusions drawn by the authors?

This helps determine the best results obtained by a research paper, helps classify the paper quality and selection more easily.

RP3: Was the study peer-reviewed and published in a reputable journal?

This helps us understand the amount of quality of the paper so that it can easily categorized into the length of priority, and to be picked or not compared to other research paper's.

2.2 Research paper grading:

RQ1: What are the types of datasets used for performing analysis on chest through CXR?

The answer to this question can provide lot of collected information precision over the amount of information to be collected to build a perfect model and to extract features.

RQ2: List of features extracted by individual members and how did they extract?

The answer to this question gives the information of individual approach towards the collected dataset and number of features they were able to extract and use it for further process in making use of it.

RQ3: Methodologies used for data preprocessing of the CXR especially?

The answer to this question helps us understand types of techniques than can be used to operate on the avoidance of data-loss on the CXR along with additional technique which we can improvise with.

RQ4: Models used for training through the pre-processed data?

Helps us understand what methodologies have worked more effectively and also help us avoid the same mistakes along with the improvisation of already existing models.

2.3 Search process

We conducted an extensive search on well-known computer science journals, google scholar , cures, Research Gate, Journal of EST etc. Where we were able to achieve valid research papers from the year 2015 to 2022. There are several other papers with some other years which are unique from the years perspective.

Search strings: We used sentences like “heart disease prediction”, “Chest map analysis", "chest X-ray analysis”.

2.4 Quality assessment

We analyzed the complete procedure of each paper individually and compared them with cross check- analysis to compare them based on 4 categories and have placed them on single table to compare the results of the methods they have applied.

Quality assessment criteria 1: Data pre-processing approach.

Quality assessment criteria 2: Data training method

Quality assessment criteria 3: Organization and accumulation of models

Quality assessment criteria 4: Output format of the final result

3. Results

3.1 RQ1: What are the types of datasets used for performing analysis on chest through CXR?

The data sets are not too different most of them are chest x-ray image from Kaggle challenge's, ChestX-Ray14, Google cloud datasets, NH, ChestX-ray8 dataset from the NIH with labels from Google.

Table 1:

Data-set Name	**Number of papers**	**Quality assessment score for 10**
Kaggle challenge	13	7
Google Cloud datasets	4	6
CHestX-ray8	1	8
NIH	2	5
CHestX-Ray14	1	8
GE	1	6
NH	1	5
ImageNet Dataset	1	7
Github Covid Repository dataset	2	9
RSNA Chestx-ray-8	1	9
Custom x-ray of 48 patients	1	7
CXR's from open download	1	5
PASP Measured Trans-thoracic	1	8
Bras-field data-set	2	10
Covid-19 CXR's	3	8
Shenzh	1	7
Montgomery	1	7
RSNA Pneumonia detection challange	2	8
PACS at ASAN medical center	1	7
Manual collection through domain website	1	6
Kermanyet al. And the Radiological Society of North America (RSNA)	1	9

Note: Many papers have used multiple datasets for comparison purposes the number may vary based on the number of papers used same type of x-rays.

The score is based on SPIDER method which states that the SPIDER method can be used to evaluate the quality and relevance of a research paper on chest X-ray analysis using deep learning. To grade a research paper using the SPIDER method, we can consider the following criteria:

1. Sample: Does the paper clearly describe the sample of individuals with chest X-rays used for the study? Is the sample representative of the population of interest and large enough to ensure robust results?
2. Phenotype: does the paper provide a clear description of the phenotype of interest, such as a specific medical condition, and how it was diagnosed or confirmed?
3. Inheritance: Does the paper discuss the potential for genetic or familial factors to influence the phenotype of interest?
4. Diagnosis: Does the paper discuss a clear description of the diagnosis criteria used to classify the phenotype of interest?
5. Exposure: Does the paper discuss any relevant environment factors or exposure that may influence the phenotype of interest?
6. Research: Does the paper provide a clear and well-designed research plan to test the hypothesis and answer the research question?

Table 2: Paper publisher grading

Data Base	**Paper count**	**Overal Quality level** **High(H),Medium(M),Low(L)**
ELSEVIER	4	H
Journal of EST	1	M
ResearchGate	1	H
Cureus	2	H
MDPI	2	H
Journal of medical systems	1	H
PLOS ONE	4	M
Articles	2	H
Academia	2	H
Radiology	4	H
The Union	1	M

Applied Intelligence	4	M
BioMedical Engineering OnLine	2	H
MedRiv	2	H
Original Article	1	M
JCSE	1	L
DIR	1	L
Nucleic Acids Research	1	M
Physical and engineering Sciences in Medicine	1	H
Social Network analysis and Mining	1	M
Nature.com	2	M
Health and Wellbeing e-Networks for All	1	M
JAMA Network	1	M
Total	42	

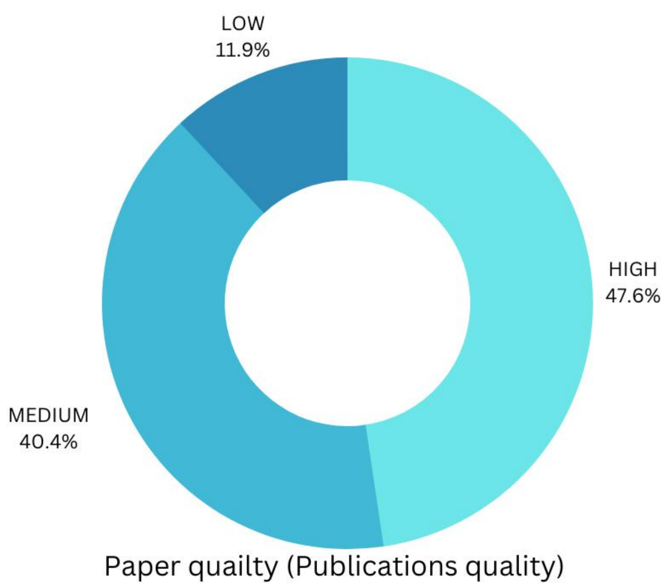

FIG:2

Reference citation	**Grade point scaled to 10**
[1]	**7**
[2]	10
[3]	**5**
[4]	**8**
[5]	**10**
[6]	**9**
[7]	**9**
[8]	**7**
[9]	**3**
[10]	**8**
[11]	**8**
[12]	**9**
[13]	**10**
[14]	**10**
[15]	**7**
[16]	**7**
[17]	**9**
[18]	**9**
[19]	**8**
[20]	**7**
[21]	**8**
[22]	**4**
[23]	**3**
[24]	**5**
[25]	**7**

[26]	**8**
[27]	**5**
[28]	**6**
[29]	**8**
[30]	**9**
[31]	**8**
[32]	**3**
[33]	**8**
[34]	**9**
[35]	**8**
[36]	**9**
[37]	**10**
[38]	**9**
[39]	**9**
[40]	**10**

Table: Paper quality grading scaled to 10 based on SPIDER.

3.2 List of features extracted by individual members and how did they extract?

There have been number of features identified and extracted they are as follows

1. **Cardiomegaly:** Cardiomegaly is typically a symptom of another illness, such as heart disease or a problem with the heart valves. It could also be an indication of a previous heart attack. Infections or pregnancy-related physiological stress can also cause it.
2. **Emphysema:**Breathlessness is a symptom of the lung disease emphysema. Alveoli, the lungs' air sacs, suffer damage in those with emphysema. The air sacs' inner walls deteriorate and tear over time, resulting in the creation of fewer, larger air gaps as opposed to more, smaller ones.

3. **Effusion:** a time when something, such a liquid or gas, is released.
4. **Hernia:** a tissue or organ protruding through an unusual hole.
5. **Infiltration:** The spread or deposition of foreign chemicals in a tissue or cell in greater quantities than usual is referred to as infiltration. Infiltrate refers to the substance that has accumulated in certain tissues or cells.

6. **Mass:** (mas) A bodily bulge as used in medicine. It could be brought on by an immunological response, a cyst, hormonal abnormalities, or aberrant cell growth. A tumour could be cancerous or benign (not cancerous) (cancer).
7. **Nodule:** (NAH-jool) a growth or tumour that could either be benign or cancerous (not cancer).
8. **Atelectasis:** (A-teh-LEK-tuh-sis) the lung's inability to fully expand (inflate). A blocked airway, a tumour, general anaesthesia, pneumonia or other lung infections, lung illness, prolonged bed rest with shallow breathing, and general anaesthesia are a few potential causes. referred to as a collapsing lung.
9. **Pneumothorax:** (NOO-moh-THOR-ax) an unusual buildup of air between the chest cavity and the thin layer of tissue that surrounds the lungs The lung may partially or completely collapse as a result. A chest injury, specific medical procedures, a lung condition, or other harm to the lung tissue can all result in a pneumothorax.
10. **Pneumonia:** A severe lung inflammation where the alveoli (tiny air sacs) are filled with fluid (noo-MOH-nyuh). The amount of oxygen that blood can absorb from air inhaled into the lung may decrease as a result of this.
11. **Fibrosis:** Fibrosis is the medical term for tissue thickening or scarring. In this situation, the normally thin, lacy walls of the lungs' air sacs no longer remain thin and lacy but instead thicken, stiffen, and scar—a condition known as fibrosis.
12. **Edema:** When too much fluid is trapped in the body's tissues, it causes swelling, or edoema.
13. **Consolidation:**An area of uniformly increased lung parenchymal attenuation known as consolidation obscures the borders of blood vessels and airway walls . There may be air bronchograms in the consolidating area.

Each of these features are extracted from various datasets across the projects but only some of them have shown analysis part of these aspects whereas most of the projects have only shown the classification part only stating the presence of abnormality is there or not.The main drawback of the projects is the provision of minimal information with lot of information intake which means the project is decisively under performing yet the models have been well trained.

The features are mostly of pneumonia which is the puss formation in the lungs, then there is edema which is the swelling of particular part, and next is cardiomegaly it is the expansion of the heart, Mass and Effusion are shown as similar feature but are irrelevant after the feature extraction because they are not shown in the output.

3.3 RQ3: Methodologies used for data preprocessing of the CXR especially?

Title(System)	Model used	Feature extraction (Approach)	Data set	Output metrics	Authors	Reference citation
Deep learning for chest X-ray analysis: A survey	CNN	image-level prediction (classification and regression), segmentation, localization, image generation and domain adaptation	Kaggle challenge	Finding the high accuracy using image-level prediction (classification and regression), segmentation, localization, image generation and domain adaptation	Çallı, E., Sogancioglu, E., van Ginneken, B., van Leeuwen, K.G. and Murphy, K.	[1]
Application of deep learning techniques for detection of COVID-19 cases using chest X-ray images: A comprehensive study	ResNet-34	CNN	Kaggle challenge	98.33%	Nayak SR, Nayak DR, Sinha U, Arora V, Pachori RB.	[2]
Pneumonia detection using CNN through chest x-ray	ANN, CNN	CNN	Kaggle challenge	Architecture 5 works better	GM H, Gourisaria MK, Rautaray SS, Pandey MA	[3]
Chest x-ray image classification in medical image analysis	ResNet-50	CNN	Chest X-Ray14	ResNet-50 achieved state-of-the-art results in four out of	Rahmat T, Ismail A, Aliman S.	[4]

				fourteen classes.		
Deep-Pneumonia Framework Using Deep Learning Models Based on Chest X-Ray Images	ResNet 152V2	CNN	Kaggle challenge	99.22%	Elshennawy NM, Ibrahim DM.	[5]
Deep-chest: Multi-classification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases	VGG19+CNN	CNN	Kaggle challenge	98.05%	Ibrahim I Elshennawy NM, Sa AM.	[6]
Pneumonia detection in chest X-ray images using an ensemble of deep learning models	GoogLeNet, ResNet-18, and Dense Net-121	convolutional neural network	Kaggle challenge	98.81%	Kundu R, Das R, Geem ZW, Han GT, Sarkar R.	[7]
Chest x-ray analysis with deep learning-based software as a triage test for pulmonary tuberculosis: a prospective study of diagnostic accuracy for culture-confirmed disease	CAD4TBv6	Deep learning based software , regression model	Kaggle challenge	High accuracy than qXRv2	Khan FA, Majidulla A, Tavaziva G, Nazish A, Abidi SK, Benedetti A, Menzies D, Johnston JC, Khan AJ, Saeed S.	[8]
Identifying Pneumonia in Chest XRays: A Deep Learning Approach	(ResNet50 + ResNet101)	Mask-RCNN	Kaggle challenge	0.218051	Jaiswal AK, Tiwari P, Kumar S, Gupta D, Khanna A, Rodrigues	[9]

					JJ.	
Chest Radiograph Interpretation with Deep Learning Models: Assessment with Radiologist-adjudicated Reference Standards and Population-adjusted Evaluation	CNN	convolutional neural networks	Google cloud, kaggle	The model demonstrated population-adjusted areas under the receiver operating characteristic curve of 0.95 (pneumothorax), 0.72 (nodule or mass), 0.91 (opacity), and 0.86 (fracture)	Majkowska Mittal S, Ste DF, Reicher McKinney Duggan Eswaran Cameron C PH, Liu Kalidindi Ding A	[10]
Detection of tuberculosis patterns in digital photographs of chest X-ray images using Deep Learning: feasibility study	ANN, ViDi classification tool, ViDi detection tool	Deep Learning image analysis software (Suite v2.0; ViDi Systems, Villaz-Saint-Pierre, Switzerland	Kaggle challenge	area under the ROC curve 0.82 & AUC 0.98	Becker AS, Blüthgen C, Sekaggya-Wiltshire C, Castelnuovo B, Kambugu A, Fehr J, Frauenfelder T. .	[11]
Deep learning based detection and analysis of COVID-19 on chest X-ray images	Xception	CNN	Kaggle challenge	97.97%	Jain R, Gupta M, Taneja S,Hemanth DJ.	[12]
A machine learningbased framework for diagnosis of COVID19 from chest Xray images	CNN +PCA	CNN	Kaggle challenge	The proposed method achieved high accuracy of 100%	Rasheed J, Hameed AA, Djeddi C, Jamil A, Al-Turjman F.	[13]

				using CNN +PCA when variance of 0.99 was used		
Machine learning classifcation of texture features of portable chest Xray accurately classifes COVID19 lung infection	XGB-linear	DCNN	Kaggle challenge	100%	Hussain L, Nguyen T, Li H, Abbasi AA, Lone KJ, Zhao Z, Zaib M, Chen A, Duong TQ.	[14]
A deep-learning pipeline for the diagnosis and discrimination of viral, non-viral and COVID-19 pneumonia from chest X-ray images	DeepLabv3	Semantic Segmentation	Kaggle challenge	DeepLabv3 outperformed both FCN and U-Net	Wang G, Liu X, Shen J, Wang C, Li Z, Ye L, Wu X, Chen T, Wang K, Zhang X, Zhou Z.	[15]
Deep learning for distinguishing normal versus abnormal chest radiographs and generalization to two unseen diseases tuberculosis and COVID19	Efcient Net-B7	CNN	NH	EfcientNet-B7 performs better than other advanced networks	Nabulsi Sellergren Jamshy S, C, Santos Kiraly AP, W, Yang Pilgrim Kazemzadeh Yu J.	[16]
Machine learning applied on chest x-ray can aid in the diagnosis of COVID-19: a first experience from Lombardy, Italy	Image analysis for deep learning classifier	CNN	aggle challenge	99%	Castiglioni I, Ippolito D, Interlenghi M, Monti CB, Salvatore C, Schiaffino S, Polidori A, Gandola	[17]

					D, Messa C, Sardanelli F.	
Pneumonia Detection and Classification Using Deep Learning on Chest X-Ray Images	ResNet 152	CNN	Kaggle challenge	97%	Darici MB, Dokur Z, Olmez	[18]
Predicting COVID-19 Pneumonia Severity on Chest X-ray With Deep Learning	Dense Net	CNN	Chest X-ray8 dataset from the NIH with labels from Google	The use of a score combining geographical extent and degree of opacity allows clinicians to compare CXR images with each other using a quantitative and objective measure.	Cohen JP, Dao L, Roth K, Morrison P, Bengio Y, Abbasi AF, Shen B, Mahsa HK, Ghassemi M, Li H, Duong TQ.	[19]
CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images	Xception Classification model	normalization	ImageNet data set	Overall accuracy of 89.6% precision and recall rate is 93% and 98.2% for 4 classes and classification accuracy is 95%	Asif Iqbal Khana,* , Junaid Latief Shahb, Mohammad Mudasir Bhat c Asif Iqbal Khana,* , Junaid Latief Shahb, Mohammad Mudasir Bhat c	[20]

AI for radiographic COVID-19 detection selects shortcuts over signal	CNN Classification model	normalization	Github Covid repository Chest x-ray14 repository	Outlined area of disease on the x-ray through generated images from the original x-reays	Alex J. DeGrave1,2, *, Joseph D. Janizek1,2,* , and Su-In Lee1,**	[21]
Public Covid-19 X-ray datasets and their impact on model bias - a systematic review of a signifificant problem		PROBAST , TRIPOD and TREE.			Beatriz Garcia Santa Cruza,b,* , Matías Nicolás Bossab , Jan Sölterb , Andreas Dominik Huschb	[22]
Predicting COVID-19 Pneumonia Severity on Chest X-ray With Deep Learning	Densenet Model from torchx-ray vision library	Normalization Image resized to 224*224 and scaled to -1024 1024	RSNA, cheXpert, chest xray8	Quantitative performance metrics-correlation is 0.8 with output of 4 labels (lung opacity, pneumonia , infiltration and consolidation)	Joseph Paul Cohen , Lan Dao , Karsten Roth , Paul Morrison , Yoshua Bengio , Almas F. Abbasi , Beiyi Shen , Hoshmand Kochi Mahsa , Marzyeh Ghassemi , Haifang Li , Tim Q.	[23]

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Determination of disease severity in COVID-19 patients using deep learning in chest X-ray images	EfficentNet @ modified U-net	Manual classification of types of x-rays	X-rays of 48 patients between the age of	Classification and output of percentage of RT-PCR results	Maxime Blain* Michael T. Kassin* Nicole Varble * Xiaosong Wang Ziyue Xu Daguang Xu Gianpaolo Carrafiello Valentina Vespro Elvira Stellato Anna Maria Ierardi Letizia Di Meglio Robert D. Suh Stephanie A. Walker Sheng Xu Thomas H. Sanford Evrim B. Turkbey Stephanie Harmon	[24]

					Baris Turkbey Bradford J. Wood	
Deep transfer learning artificial intelligence accurately stages COVID-19 lung disease severity on portable chest radiographs	CNN, VGG16.	Five-fold cross validation	CXR images from open download	Predicted vs radiology scores,correlation analysis,mean absolute error analysis are optimal to the research previous papers	Jocelyn Zhu, Beiyi Shen, Almas Abbasi, Mahsa Hoshmand-Kochi, Haifang Li, Tim Q. Duong	[25]
A promising approach for screening pulmonary hypertension based on frontal chest radiographs using deep learning: A retrospective study	Resnet 50, xception, inception v3	tune learning rate to 0.0008 according to the best score on validation data.	PASP measured Doppler transthoracic echocardiography from 762 patients (357 healthy contr	The AUC performed by the best model (Inception V3) achieved 0.970 in the internal test, and slightly declined in the external test (0.967) when using deep learning algorithms	Xiao-Ling Zou1☯, Yong Ren2☯, Ding-Yun Feng1, Xu-Qi He3, Yue-Fei Guo4, Hai-Ling Yang1, Xian Li5, Jia Fang6, Quan Li2, Jun-Jie Ye2, Lan-Qing Han2☯*, Tian-Tuo Zhang1☯*	[26]

			ols and 405 with PH) from three institutes in China from January 2013 to May 2019	to classify PH from normal based on chest X-rays. The mean absolute error (MAE) of the best model for prediction of PASP value was smaller in the internal test (7.45) compared to 9.95 in the external test		
Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study	CNN	A cross-sectional design with multiple model training cohorts was used to evaluate model generalizability to external sites using	chest X-rays from the National Institutes of Health Clinical Cente	Pneumonia-screening CNNs achieved better internal than external performance in 3 out of 5 natural comparisons. When models	John R. Zech 1☯, Marcus A. Badgeley 2☯, Manway Liu 2, Anthony B. Costa 3, Joseph J. Titano4, Eric Karl Oermann 3*	[27]

		split-sample validation. A total of 158,323 chest radio graphs were drawn from three institutions	r	were trained on pooled data from sites with different pneumonia prevalence		
Artificial Intelligence-Based Diagnosis of Cardiac and Related Diseases	Mask-Rcnn Resnet	Feature pyramid network decoder	CXR images	Semantic segmentation and output mask of input CXR images	Muhammad Arsalan , Muhammad Owais , Tahir Mahmood , Jiho Choi and Kang Ryoung Park *	[28]
Deep learning to automate Brasfifield chest radiographic scoring for cystic fifibrosis	DCNN model Resnet -18	XR650 digital radiography system	Bras-field datasets	Accuracy of 90.3% Correlation of 0.79 - 0.83	Evan J. Zuckera,* , Zachary A. Barnesb, Matthew P. Lungrena, Yekaterina Shpanskaya a, Jayne M. Seekinsa, Safwan S. Halabia, David B. Larsona	[29]

Diagnosis of Corona-virus Disease 2019 Pneumonia by Using Chest Radiography: Value of Artificial Intelligence	CV19-net	(ACU) Area under characteristic curve used to differentiate based on disease and date taken from certasin period of time to fixed period of time.	Covid-19 chest x-ray	Accuracy of 94% and was able to classify the items from 2019 pneumonia to other related pneumonia	*Ran Zhang, PhD • Xin Tie, BS • Zhihua Qi, PhD • Nicholas B. Bevins, PhD • Chengzhu Zhang, MS • Dalton Griner, MS • Thomas K. Song, MD • Jeffrey D. Nadig, MD • Mark L. Schiebler, MD • John W. Garrett, PhD • Ke Li, PhD • Scott B. Reeder, MD, PhD • Guang-Hong Chen, PhD*	[30]
Ensemble learning based automatic detection of tuberculosis in chest X-ray images using hybrid feature descriptors	CNN with enseamble learning	K-fold cross validation scheme and rezied images to 300 * 300	Shenzhen and Montgomery datasets	Achieved 80% accuracy through the model valuation at model evaluation	Muhammad Ayaz1 · Furqan Shaukat2 · Gulistan Raja1	[31]

Synthesis of COVID-19 chest X-rays using unpaired image-to-image translation	VGG-16 and ResNet-50	Normalization and resize of images to 256 * 256 and scaled pixel value to [0,1]	RSNA Pneumonia detection challenge datasets with CXR'S	Model evaluation and comparison shown through using the two models no accuracy achieved as for the work nature	Hasib Zunair1 · A. Ben Hamza	[32]
Reproducibility of abnormality detection on chest radiographs using convolutional neural network in paired radiographs obtained within a short-term interval	CNN	normalization	PACS at ASAN medical center all CXR's With MRI scans	Image output with coloured outlined box around the affected area but with minimal exposure and enhancement	Yongwon Cho1,4, Young-Gon Kim1,4, Sang Min Lee3*, Joon Beom Seo3 & Namkug Kim	[33]
A deep learning-based model for screening and staging pneumoconiosis	U-Net semantic segmentation with Res-net as backbone	2 stages of image reading with final dropped images with	Manual collection of data-set through their domain websi	Achieved accuracy of 92% with	Liuzhuo Zhang1,2,7, Ruichen Rong2,7, Qiwei Li3,7, Donghan M.Yang2 , BoYao2 , Danni Luo2 , Xiong	[34]

			tes through user registrations.		Zhang1 , Xianfeng Zhu4 , Jun Luo1 , Yongquan Liu4 , XinyueYang 1,5, Xiang Ji1 , Zhidong Liu6 , Yang Xie2 , Yan Sha1 , Zhimin Li1,5* & Guanghua Xiao2*	
Identifying Cardiomegaly in ChestX-ray8 Using Transfer Learning	Transfer learning	Images re-sized to (224,224) with dimension 3	Chest X-ray8 data-set issued by NIH	Histogram equalization and cropped images of gray scale images	Sicheng Zhoua, Xinyuan Zhangb, Rui Zhanga,c	[35]

Pneumonia detection in chest X-ray images using an ensemble of deep learning models	GoogLeNet, ResNet-18, and DenseNet-121	Deep learning model	Kermany et al. and the Radiologi cal Society of North America (RSNA)	Obtained an accuracy rate of 98.81 %, a sensitivity rate of 98.80 %, a precisi	Kundu R, Das R, Geem ZW, Han GT, Sarkar R.	[36]

				on rate of 98.82 %, and an f1-score of 98.79 % on the Kermany dataset and an accuracy rate of 86.86 %, a sensitivity rate of 87.02 %, a precision rate of 86.89 %,		
Covid-19 Classification Using Deep Learning in Chest X-Ray Images	ResNet - 50	Deep learning model		Accuracy rate of 99.5%	Karhan Z, Fuat AK.	[37]
Deep Learning Approach for Analyzing the COVID-19 Chest	VGG 16	Deep learning model	Kaggle	Accuracy 94.96 %	Manav M, Goyal M, Kumar A, Arya AK, Singh H, Yadav AK.	[38]

X-Rays						

Pneumothorax detection in chest radiographs using convolutional neural networks	CNN	Deep learning model	Google Cloud	Acquired AUC with values between 0. 92 and 0. 96	Blumenfeld A, Konen E, Greenspan H.	[39]
A deep learning approach for classification of COVID and pneumonia using DenseNet-201	Dense Net - 121	Deep learning model	Kaggle	accuracy of 99.1%, sensitivity of 98.5%, and specificity of 98.95 %.	Sanghvi HA, Patel RH, Agarwal A, Gupta S, Sawhney V, Pandya AS.	[40]

3.4 RQ4: Models used for training through the pre-processed data?

The most common models used for the training is CNN, Resnet18, VGG-16, ResNet-34, 50.

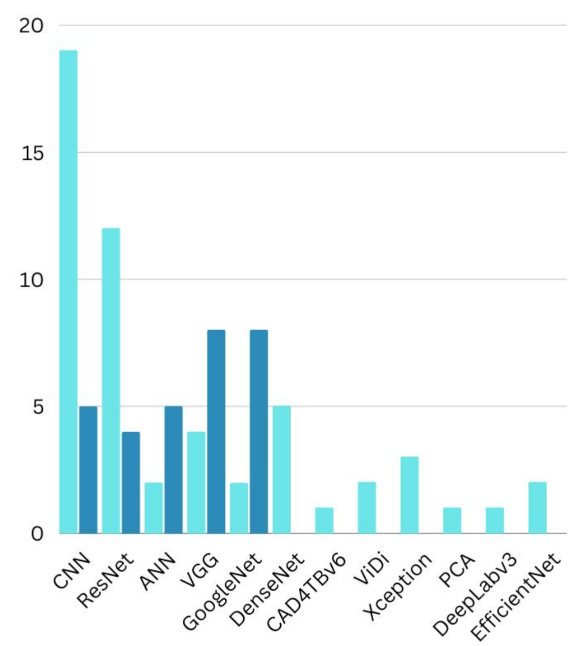
Now let's look at the number of papers that have been involved in these models.

Type of model	Number of papers
CNN	19
ResNet-34,50,15,18,5	12
ANN	2
VGG19,16	4
Google Net	2
Dense Net	5
CAD4TBv6	1

ViDi	1
Xception	3
PCA	1
DeepLabv3	1
EfficientNet-B7	2

Type of model	Number of papers
CNN	[1],[3],[6],[10],[13],[17],[21],[25],[27],[31],[33],[39]
ResNet-34,50,15,18,5	[2],[4],[5],[7],[9],[18],[26],[28],[29],[32],[34],[36],[37]
ANN	[3],[11]
VGG19,16	[6],[25],[32],[38]
Google Net	[7],[36]
Dense Net	[7],[19],[23],[36],[40]
CAD4TBv6	[8]
ViDi	[11]
Xception	[12],[20],[26]
PCA	[13]
DeepLabv3	[15]
EfficientNet-B7	[16],[24]
XGB Linear	[14]
CV-19	[30]
Inception V3	[26]

Fig.3: Models used



3.5 Challenges/Limitations in the current research?

According to the scrutinization of all the papers collected we can clearly state there are 5 drawbacks they are:

1: Data Pre-Processing techniques.

2: less data availability of data to perform necessary operations after Pre-processing.

3: Most of them are classification projects and models.

4: Analysis models with less accuracy.

5: Output method indecisive.

3.5.1 In the collected papers we have observed data pre-processing techniques like normalization, image localization and such conventional techniques which are same as other projects and research done by others so the result is almost same as others and there is not much difference and most of the dataset are also being used same so the issue arises over there.

The most of the parts due to the type of data – preprocessing additional data which need to be added is made difficult and they can't add it without training the whole model again.

[4],[16],[19].[22],[23],[26],[28],[29],[39]

Not only that the images which are being neglected with slite deviation from the mean gradient are most valuable to variate the best and worst image but they are being completely ignored which is leading to less model accuracy too.

The unprecedented intent of wanting to preserve the epoch iteration is the main cause for such uncertainty on the data training in the projects

These challenges can be overcome by simply using alternative techniques which involve either hybrid methodologies or which can adapt based on the data being input.

3.5.3 Most of them are classification projects and models.

The main issue of the output is that they are predicting the output to be yes or no but aren't justifying through any means of representation of the result.

This counts to untrust worthy output the issue can be overcome if there is either metric value representation of the disease of anomaly according to average rate of threshold limit for that specific anomaly or visual representation through heat map or spot marking over the input image which helps in better understanding of the output and easy justification is made.

[1],[2],[4],[6],[9],[10],[13],[15],[16],[17],[20],[21],[23]

3.5.4 Analysis models with less accuracy.

The logistic models have the best accuracy compared to the analysis models which is another drawback to be reckoned with caution, the main goal of the project is to give accurate output of the x-ray analysis so it makes an important mark on the performance of the model.

To overcome this problem, the amount epoch needs to be efficient which is possible by proper division of data and addition of data continuously to train the data more and achieve more accuracy

[3],[5],[7],[8],[11],[12],[14],[18],[19],[22]

3.5.5 Output method indecisive.

The end result of the project is undeceived with the vanishing gradient problem and all the project are to be run through terminal there is no UI/UX or basic GUI to be used as a working prototype.

[1],[3],[4],[5],[11],[14],[18],[23],[24],[29],[33]

The projects done only for the sake of research purpose have proven their domain point on the target that they have placed but hasn't addresses the main issues which come as a ricochet again, when others perform the same task with different guidelines and set targets.

CONCLUSION:

The obsereved models are mostly limited and are commonly used a lot.

So, there is a scope of implementing other models like transfer learning and other architectures of CNN or other models

4. References:

[1] Deep learning for chest X-ray analysis: A survey

Çallı, E., Sogancioglu, E., van Ginneken, B., van Leeuwen, K.G. and Murphy, K.

[2] Application of deep learning techniques for detection of COVID-19 cases using chest X-ray images: A comprehensive study

Nayak SR, Nayak DR, Sinha U, Arora V, Pachori RB.

[3] PNEUMONIA DETECTION USING CNN THROUGH CHEST X-RAY

GM H, Gourisaria MK, Rautaray SS, Pandey MA

[4] CHEST X-RAYS IMAGE CLASSIFICATION IN MEDICAL IMAGE ANALYSIS

Rahmat T, Ismail A, Aliman S.

[5] Deep-Pneumonia Framework Using Deep Learning Models Based on Chest X-Ray Images

Elshennawy NM, Ibrahim DM.

[6] Deep-chest: Multi-classification deep learning model for diagnosing COVID-19, pneumonia, and lung cancer chest diseases

Ibrahim DM, Elshennawy NM, Sarhan AM.

[7] Pneumonia detection in chest X-ray images using an ensemble of deep learning models

Kundu R, Das R, Geem ZW, Han GT, Sarkar R.

[8] Chest x-ray analysis with deep learning-based software as a triage test for pulmonary tuberculosis: a prospective study of diagnostic accuracy for culture-confirmed disease

Khan FA, Majidulla A, Tavaziva G, Nazish A, Abidi SK, Benedetti A, Menzies D, Johnston JC, Khan AJ, Saeed S.

[9] Identifying Pneumonia in Chest XRays: A Deep Learning Approach

Jaiswal AK, Tiwari P, Kumar S, Gupta D, Khanna A, Rodrigues JJ.

[10] Chest Radiograph Interpretation with Deep Learning Models: Assessment with Radiologist-adjudicated Reference Standards and Population-adjusted Evaluation

Majkowska A, Mittal S, Steiner DF, Reicher JJ, McKinney SM, Duggan GE, Eswaran K, Cameron Chen PH, Liu Y, Kalidindi SR, Ding A

[11] Detection of tuberculosis patterns in digital photographs of chest X-ray images using Deep Learning: feasibility study

Becker AS, Blüthgen C, Sekaggya-Wiltshire C, Castelnuovo B, Kambugu A, Fehr J, Frauenfelder T. .

[12] Deep learning based detection and analysis of COVID-19 on chest X-ray images

Jain R, Gupta M, Taneja S,Hemanth DJ.

[13] A machine learning based framework for diagnosis of COVID19 from chest Xray images

Rasheed J, Hameed AA, Djeddi C, Jamil A, Al-Turjman F.

[14] Machine learning classifcation of texture features of portable chest Xray accurately classifes COVID19 lung infection

Hussain L, Nguyen T, Li H, Abbasi AA, Lone KJ, Zhao Z, Zaib M, Chen A, Duong TQ.

[15] A deep-learning pipeline for the diagnosis and discrimination of viral, non-viral and COVID-19 pneumonia from chest X-ray images

Wang G, Liu X, Shen J, Wang C, Li Z, Ye L, Wu X, Chen T, Wang K, Zhang X, Zhou Z.

[16] Deep learning for distinguishing normal versus abnormal chest radiographs and generalization to two unseen diseases tuberculosis and COVID19

Nabulsi Z, Sellergren A, Jamshy S, Lau C, Santos E, Kiraly AP, Ye W, Yang J, Pilgrim R, Kazemzadeh S, Yu J.

[17] Machine learning applied on chest x-ray can aid in the diagnosis of COVID-19: a first experience from Lombardy, Italy

Castiglioni I, Ippolito D, Interlenghi M, Monti CB, Salvatore C, Schiaffino S, Polidori A, Gandola D, Messa C, Sardanelli F.

[18] Pneumonia Detection and Classification Using Deep Learning on Chest X-Ray Images

Darici MB, Dokur Z, Olmez

[19] Predicting COVID-19 Pneumonia Severity on Chest X-ray With Deep Learning

Cohen JP, Dao L, Roth K, Morrison P, Bengio Y, Abbasi AF, Shen B, Mahsa HK, Ghassemi M, Li H, Duong TQ.

[20] CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images

Asif Iqbal Khana,∗, Junaid Latief Shahb, Mohammad Mudasir Bhat c

[21] AI for radiographic COVID-19 detection

selects shortcuts over signal

Alex J. DeGrave1,2,*, Joseph D. Janizek1,2,*, and Su-In Lee1,**

[22] Public Covid-19 X-ray datasets and their impact on model bias - a systematic review of a

signifificant problem

Beatriz Garcia Santa Cruza,b,∗ , Matías Nicolás Bossab , Jan Sölterb , Andreas Dominik Huschb

[23] Predicting COVID-19 Pneumonia Severity on

Chest X-ray With Deep Learning

Joseph Paul Cohen , Lan Dao , Karsten Roth , Paul Morrison , Yoshua Bengio , Almas F. Abbasi ,

Beiyi Shen , Hoshmand Kochi Mahsa , Marzyeh Ghassemi , Haifang Li , Tim Q. Duong.

[24] Determination of disease severity in COVID-19 patients using deep

learning in chest X-ray images

Maxime Blain*

Michael T. Kassin*

Nicole Varble *

Xiaosong Wang

Ziyue Xu

Daguang Xu

Gianpaolo Carrafiello

Valentina Vespro

Elvira Stellato

Anna Maria Ierardi

Letizia Di Meglio

Robert D. Suh

Stephanie A. Walker

Sheng Xu

Thomas H. Sanford

Evrim B. Turkbey

Stephanie Harmon

Baris Turkbey

Bradford J. Wood

[25] Deep transfer learning artificial intelligence
accurately stages COVID-19 lung disease
severity on portable chest radiographs
Jocelyn Zhu, Beiyi Shen, Almas Abbasi, Mahsa Hoshmand-Kochi, Haifang Li, Tim
Q. DuongID

[26] A promising approach for screening
pulmonary hypertension based on frontal
chest radiographs using deep learning: A
retrospective study
Xiao-Ling Zou1☯, Yong Ren2☯, Ding-Yun Feng1, Xu-Qi He3, Yue-Fei Guo4, Hai-Ling Yang1,
Xian Li5, Jia Fang6, Quan Li2, Jun-Jie Ye2, Lan-Qing Han2☯*, Tian-Tuo Zhang1☯*

[27] Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study

John R. ZechID1☯, Marcus A. BadgeleyID2☯, Manway LiuID2, Anthony B. CostaID3, Joseph

J. Titano4, Eric Karl OermannID3*

[28] Artifificial Intelligence-Based Diagnosis of Cardiac and

Related Diseases

Muhammad Arsalan , Muhammad Owais , Tahir Mahmood , Jiho Choi and

Kang Ryoung Park *

[29] Deep learning to automate Brasfifield chest radiographic scoring for

cystic fifibrosis

Evan J. Zuckera,∗, Zachary A. Barnesb, Matthew P. Lungrena, Yekaterina Shpanskayaa,

Jayne M. Seekinsa, Safwan S. Halabia, David B. Larsona

[30] Diagnosis of Corona-virus Disease 2019 Pneumonia by

Using Chest Radiography: Value of Artificial Intelligence

Ran Zhang, PhD • Xin Tie, BS • Zhihua Qi, PhD • Nicholas B. Bevins, PhD • Chengzhu Zhang, MS •

Dalton Griner, MS • Thomas K. Song, MD • Jeffrey D. Nadig, MD • Mark L. Schiebler, MD •

John W. Garrett, PhD • Ke Li, PhD • Scott B. Reeder, MD, PhD • Guang-Hong Chen, PhD

[31] Ensemble learning based automatic detection of tuberculosis in chest

X-ray images using hybrid feature descriptors

Muhammad Ayaz1 · Furqan Shaukat2 · Gulistan Raja1

[32] Synthesis of COVID 19 chest X rays using unpaired image to image

translation

Hasib Zunair1 · A. Ben Hamza

[33] Reproducibility of abnormality
detection on chest radiographs
using convolutional neural network
in paired radiographs obtained
within a short term interval
Yongwon Cho1,4, Young Gon Kim1,4, Sang Min Lee3*, Joon Beom Seo3 & Namkug Kim

[34] A deep learning based model for screening and staging neumoconiosis
Liuzhuo Zhang1,2,7, Ruichen Rong2,7, Qiwei Li3,7, Donghan M.Yang2 , BoYao2 , Danni Luo2 ,
Xiong Zhang1 , Xianfeng Zhu4 , Jun Luo1 , Yongquan Liu4 , XinyueYang1,5, Xiang Ji1 ,
Zhidong Liu6 , Yang Xie2 , Yan Sha1 , Zhimin Li1,5* & Guanghua Xiao2*

[35] Identifying Cardiomegaly in ChestX-ray8 Using Transfer Learning
Sicheng Zhoua, Xinyuan Zhangb, Rui Zhanga,c

[36] Pneumonia detection in chest X-ray images using an ensemble of deep learning models
Kundu R, Das R, Geem ZW, Han GT, Sarkar R.

[37] Covid-19 Classification Using Deep Learning in Chest X-Ray Images
Karhan Z, Fuat AK.

[38] Deep Learning Approach for Analyzing the COVID-19 Chest X-Rays
Manav M, Goyal M, Kumar A, Arya AK, Singh H, Yadav AK.

[39] Pneumothorax detection in chest radiographs using convolutional neural networks
Blumenfeld A, Konen E, Greenspan H.

[40] A deep learning approach for classification of COVID and pneumonia using DenseNet-201
Sanghvi HA, Patel RH, Agarwal A, Gupta S, Sawhney V, Pandya AS.