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Computer-Aided Diagnosis (CAD) for Chest X-Rays Using Artificial Intelligence: An Overview

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ABSTRACT: Chest X-rays (CXRs) are the most commonly performed diagnostic imaging tests worldwide. However, accurately interpreting them requires significant expertise, and misdiagnoses can lead to severe consequences. Computer-Aided Diagnosis (CAD) systems powered by artificial intelligence (AI) and deep learning (DL) have emerged as promising tools to assist radiologists in detecting abnormalities such as pneumonia, tuberculosis, lung nodules, and COVID-19. This paper explores recent advancements in AI-based CXR analysis, discussing key methodologies, challenges, and future directions in CAD for chest radiography.

Index Terms:- **Artificial Intelligence, Chest X-ray (CXR), Computer-Aided Diagnosis (CAD), Convolutional Neural Networks (CNN), Deep Learning, Medical Imaging.**

I. INTRODUCTION

Chest radiography, commonly known as chest X-ray (CXR), is one of the most widely used diagnostic imaging methods in clinical practice. It plays a crucial role in diagnosing and managing a wide range of pulmonary and cardiac conditions, including pneumonia, tuberculosis, lung cancer, COVID-19, and congestive heart failure [1]. However, interpreting CXRs is a complex task that requires considerable expertise. Even experienced radiologists are prone to errors due to subtle findings, variability in image quality, and fatigue [1]. To improve diagnostic accuracy and decrease radiologist workload, Computer-Aided Diagnosis (CAD) systems have been developed as supplementary tools in radiological workflows [2]. These systems utilize machine learning and deep learning techniques to automatically detect and classify abnormalities on medical images. Recently, deep convolutional neural networks (CNNs) have demonstrated significant potential in analyzing CXRs, achieving results that approach, or in some cases even surpass, human experts [3]. CAD systems for chest X-rays aim to identify key abnormalities such as infiltrates, effusions, nodules, and cardiomegaly. Large annotated datasets such as NIH ChestX-ray14 [4] and CheXpert [5] have enabled the training of robust models that can generalize across diverse populations and imaging conditions. These systems are increasingly being incorporated into clinical practice, especially in resource-limited settings where expert radiologists may not be readily available. Despite the potential of AI [6], [7] and AI-enabled CADs in healthcare [8]–[10] long-standing efforts to adopt these technologies face several challenges, including issues related to interpretability, generalizability, regulatory approval, and integration with existing health information systems [11]. Ongoing research continues to address these challenges, with the goal of developing reliable, transparent, and clinically validated diagnostic tools.

This manuscript presents a study on:

- AI techniques used in CXR diagnosis.
- Publicly available datasets for training models.
- Clinical applications (pneumonia, TB, lung cancer, COVID-19).
- Challenges and limitations of current CAD systems.
- Future trends in AI-assisted radiology.

The remainder of the paper is structured as follows: Section 2 discusses the AI techniques employed in chest X-ray (CXR) analysis. Section 3 outlines publicly available datasets for training models. Section 4 focuses on the clinical applications of these technologies. Section 5 addresses the challenges and limitations faced by current Computer-Aided Diagnosis (CAD) systems. Future trends in AI-assisted radiology are explored in Section 6. Finally, Section 7 provides a conclusion to the paper.

II. AI TECHNIQUES USED IN CXR ANALYSIS

2.1 Traditional Machine Learning

Chest X-ray (CXR) analysis is a fundamental diagnostic tool in radiology, aiding in the detection of conditions such as pneumonia, tuberculosis, lung nodules, and other pulmonary abnormalities [1]. Traditional machine learning (ML) techniques have significantly contributed to automating and enhancing CXR interpretation, offering improved accuracy, efficiency, and scalability compared to manual assessment [12]. Key steps in traditional ML-Based CXR analysis are as mentioned below:

i. **Preprocessing** – Enhancing image quality by removing noise, standardizing contrast, and segmenting regions of interest (e.g., lung fields) [13].

ii. **Feature Extraction** – Deriving meaningful features using techniques such as:

- **Handcrafted features**: Texture descriptors (Haralick features, Local Binary Patterns), shape-based features, and histogram-based intensity features [14].
- **Transform-based methods**: Wavelets [15], Gabor filters, or Fourier transforms to capture spatial-frequency information.

iii. **Feature Selection** – Reducing dimensionality using methods like Principal Component Analysis (PCA) [16], Linear Discriminant Analysis (LDA), or mutual information-based selection.

iv. **Classification** – Applying supervised learning models such as Support Vector Machines (SVM) [17], Random Forests & Decision Trees [18], k-Nearest Neighbors (k-NN) [19] and Logistic Regression [20].

Traditional machine learning techniques face key challenges, including a reliance on feature engineering, which may not generalize well. They also struggle with adaptability to complex patterns compared to deep learning. Additionally, data imbalance requires careful management to avoid bias towards majority classes [8] .

Despite the rise of deep learning, traditional ML remains relevant in scenarios with limited data, where interpretability is crucial, or when computational resources are constrained [21]. Hybrid approaches combining traditional ML with deep features (e.g., using CNN-extracted features with SVM) have also shown promise in improving diagnostic accuracy [3].

2.2 Deep Learning

Deep learning has revolutionized medical image analysis, particularly in the interpretation of CXRs. These AI-powered systems can assist radiologists by detecting abnormalities, prioritizing urgent cases, and providing second opinions. This section covers the following primary deep learning architectures used in CXR analysis.

- CNN-based models (CheXNet,, COVID-Net)
- Vision Transformers (ViTs)
- Hybrid models combining CNNs with attention mechanisms

2.2.1 CNN-based models (CheXNet, COVID-Net)

For medical image analysis, CNNs automatically learn hierarchical features from images through convolutional layers. Particular applications include pneumonia detection, tuberculosis screening, lung nodule identification, and COVID-19 diagnosis. The pre-trained models, especially DenseNet-121 [22] due to efficient feature reuse, ResNet [23]solving the vanishing gradient problem with skip connections, and EfficientNet [24] for balancing accuracy and computational efficiency, are some common examples used in CXR analysis. CheXNet is a 121-layer Dense Convolutional Network (DenseNet) trained on the ChestX-ray 14 dataset, where the final fully connected layer has been replaced with one that has a single output with a sigmoid nonlinearity function.

The global spread of Coronavirus Disease 2019 (COVID-19), caused by the novel severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has created unprecedented challenges for public health systems around the world. Quick and precise screening methods are essential for managing the virus's spread. Although reverse transcription polymerase chain reaction (RT-PCR) is the gold standard for diagnosing COVID-19, it is often slow, resource-heavy, and prone to false negatives [25]. As an alternative or complementary approach, chest radiography, especially chest X-rays (CXRs), has been employed to detect and monitor pneumonia caused by COVID-19, owing to its speed, accessibility, and cost-effectiveness.

To aid radiologists and healthcare professionals, researchers have created various artificial intelligence (AI) systems for automated detection of COVID-19 from CXR images. Among these, COVID-Net [25] is notable as one of the first and most significant deep learning models specifically crafted for this task. Launched by Wang and Wong (2020), COVID-Net features a specialized convolutional neural network (CNN) architecture developed through machine-driven design exploration, with the goal of attaining high accuracy, efficiency, and interpretability in diagnosing COVID-19 from chest radiographs.

COVID-Net was developed using the open-access COVIDx dataset, which combines publicly sourced CXR images of normal lungs, non-COVID pneumonia, and COVID-19 cases. The model demonstrated competitive performance and was made available with its training data and codebase, fostering transparency and collaborative research during the pandemic [25]. Later iterations and extensions of COVID-Net (such as COVID-Net CXR-2) enhanced its robustness, broadened the dataset, and incorporated explainability features like GSInquire, emphasizing regions crucial for diagnosis [25].

Although COVID-Net shows potential as a screening tool, it still faces challenges related to dataset biases, the ability to generalize across different populations and imaging systems, and regulatory acceptance. Nevertheless, it marks a significant achievement in applying AI for pandemic response and has opened doors for the ongoing development of interpretable deep learning models in medical imaging.

2.2.2 Vision Transformers (ViTs)

Convolutional Neural Networks (CNNs) have traditionally played a crucial role in computer-aided diagnosis (CAD) systems for interpreting CXR, primarily due to their ability to learn spatial hierarchies and local patterns in image data. However, advancements in deep learning have introduced Vision Transformers (ViTs) into medical image analysis, including CXRs. ViTs, which substitute convolutions with self-attention mechanisms, were originally created for natural image classification [26] and have demonstrated remarkable performance on large-scale image datasets, frequently outperforming CNNs when pre-trained on extensive datasets and fine-tuned effectively. Unlike CNNs that depend heavily on local receptive fields, ViTs capture global dependencies through multi-head self-attention, enabling them to understand long-range contextual relationships within an image, an advantage particularly useful in medical imaging tasks where subtle and spatially dispersed anomalies frequently occur. Nonetheless, ViTs face challenges such as increased computational demands, a hunger for data, and lower interpretability compared to CNNs. Ongoing research is tackling these issues with strategies like self-supervised pretraining, hierarchical tokenization, and domain-specific architectural modifications.

2.2.3 Hybrid models combining CNNs with attention mechanisms

Hybrid models (such as ResNet + Attention [27] are gaining popularity very quickly. Attention mechanisms enhance CNNs by allowing the model to focus on diagnostically relevant regions in chest X-rays while suppressing irrelevant background noise. Spatial attention, channel attention, self attention and transformer based attention are the key approaches used for the purpose. These models improve interpretability and performance in tasks such as disease classification, localization, and segmentation.

2.3 Explainability & Uncertainty Estimation

Explainable AI (XAI) encompasses methods that render AI model decisions understandable to humans. In CXR analysis, XAI is vital as clinicians must trust AI predictions prior to their implementation in clinical practice. Regulatory requirements (such as the FDA and the EU AI Act) [28], [29] necessitate transparency in medical AI, while bias detection aids in pinpointing whether models are concentrating on irrelevant features, like scanner artifacts rather than actual lung pathology. Following are the main categories of XAI methods applied to deep learning models:

2.3.1 Gradient-weighted Class Activation Mapping (GRAD-CAM)

Grad-CAM is a popular visualization technique for understanding which regions of an input image are most important for a convolutional neural network's (CNN) predictions. It was introduced in 2017 as an extension to the Class Activation Mapping (CAM) approach, providing more general applicability across different CNN architectures. This technique explain model decisions after training, which highlight the pixels that most influence predictions [30]. In COVID-Net, Grad-CAM was used to generate visual explanations showing the lung regions contributing most to a COVID-19 positive prediction [25]. This helped validate whether the model’s attention matched radiological understanding.

2.3.2 Local Interpretable Model-agnostic Explanations (LIME)

LIME is a widely used model-agnostic explainability method aimed at interpreting individual predictions made by black-box machine learning models, such as deep neural networks, random forests, or proprietary AI systems. It functions by locally approximating the complex model’s behavior around a specific prediction through an interpretable surrogate model, like linear regression or decision trees. It alters the input to observe changes in predictions [31].

2.3.3 SHapley Additive exPlanations (SHAP)

SHAP is a comprehensive framework for interpreting machine learning models, grounded in game theory (specifically, Shapley values). It offers both global and local explanations by measuring the impact of individual features on a model’s predictions [32]. Various adaptations of SHAP exist, including TreeSHAP, KernelSHAP, DeepSHAP, and LinearSHAP.

III. MAJOR PUBLIC CXR DATASETS

High-quality, large-scale annotated datasets are crucial for effectively training robust AI models. The availability of public datasets on chest X-rays (CXRs) has significantly advanced research in Computer-Aided Diagnosis (CAD) by offering standardized benchmarks. Table 1 evaluates the primary CXR datasets, highlighting their strengths, limitations, and applications in AI model development.

IV. CLINICAL APPLICATIONS OF CAD IN CXR ANALYSIS

Chest X-rays are the primary imaging method for diagnosing a range of thoracic diseases. However, interpreting CXRs can be difficult, time-consuming, and subject to variability, even among seasoned radiologists [33]. CAD systems in CXR have shown significant promise in improving diagnostic accuracy and workflow efficiency in radiology. The following are key clinical applications:

4.1 Pneumonia Detection

CheXNet [3] was developed to assist radiologists in accurately detecting pneumonia and potentially other thoracic conditions. This innovative deep learning model employs convolutional neural networks (CNNs) for automated pneumonia diagnosis from chest X-ray (CXR) images. Created by Stanford University researchers, it is a pioneering effort in applying deep learning to medical image analysis, demonstrating performance comparable to that of human specialists.

Built on the DenseNet-121 framework, CheXNet features 121 layers of densely linked convolutional blocks and utilizes transfer learning from ImageNet to enhance convergence. It includes a fully connected layer optimized for multi-label classification of 14 thoracic diseases, trained on the NIH ChestX-ray14 dataset [5], which contains over 112,000 X-rays from more than 30,000 patients.

While primarily focused on pneumonia detection, CheXNet can be adapted for other conditions. Its performance in detecting pneumonia matches or slightly exceeds that of practicing radiologists, as measured by the F1 score. Visual explanation techniques like Grad-CAM were used to highlight areas in images that influenced the model's predictions.

Table 1: CXR Datasets

Dataset	Source	Size	Labels	Format	Applications	Limitations
NIH ChestX-ray14 [4]	National Institutes of Health (NIH) Clinical Center	112,120 frontal-view CXRs from 30,805 patients	14 common thoracic pathologies (e.g., *Atelectasis*, *Cardiomegaly, Effusion, Pneumonia*)	Multi-label classification (CheXNet, CheXpert). Weakly supervised localization (e.g., Class Activation Maps)	Multi-label classification (CheXNet, CheXpert). Weakly supervised localization (e.g., Class Activation Maps)	No pixel-level annotations (bounding boxes/masks). Label noise due to NLP extraction from reports
CheXpert [5]	Stanford University	224,316 CXRs from 65,240 patients	14 pathologies, including uncertainty labels (e.g., "uncertain fracture"	Annotated labelling using NLP on radiology reports. Includes lateral and frontal views	Uncertainty modeling in AI diagnosis. Benchmark for multi-label classification	No segmentation masks. Biased toward U.S. patient demographics
MIMIC-CXR [34], [35]	ICU patients at Beth Israel Deaconess Medical Center	377,110 CXRs + 227,827 radiology reports	14 pathologies (similar to CheXpert)	Linked with EHR data (clinical notes, vital signs). Supports multimodal AI (imaging + clinical text)	Prognostic modeling (e.g., mortality prediction). Joint image-text analysis (e.g., contrastive learning)	ICU patient bias (severe cases). No pixel-level annotations
PadChest [36]	San Juan Hospital, Spain	160,000 CXRs with 174,000 annotated findings	27 anatomic locations + 189 pathologies (most comprehensive)	Manual annotations by radiologists (higher accuracy). Includes rare diseases (e.g., pneumothorax, TB)	Rare disease detection. Localization tasks (bounding boxes available)	Smaller than NIH/CheXpert. Language bias (Spanish reports)
COVID-19 Specific Datasets [37], [38]	COVIDx (Cohen et al., 2020)	13,975 CXRs (COVID-19 + bacterial/viral pneumonia)	Used in COVID-Net	3,000+ CXRs with pixel-level annotations	BIMCV-COVID-19+ (Spain)	Small, imbalanced datasets (early-pandemic bias)

4.2 Tuberculosis (TB) Screening

qXR by Qure.ai is a validated AI tool designed for tuberculosis (TB) screening in areas with a high disease burden and limited resources [39], [40]. It demonstrates an impressive sensitivity of approximately 95% and a specificity of around 80% in identifying TB-related abnormalities, often surpassing some human readers in critical situations. Key features of qXR for TB detection include its ability to identify pulmonary infiltrates, cavities, pleural effusions, and hilar lymphadenopathy, which are common radiological indicators of TB. The system assigns a probability score indicating whether a case is "TB-suspicious" or "TB-unlikely," thereby aiding in case prioritization.

4.3 Lung Nodule & Cancer Detection

AI-driven CAD systems like qXR and Lunit INSIGHT CXR [41] greatly enhance the detection rates of lung nodules in chest X-rays, especially for early-stage lung cancer and TB screening. Although CT scans are still considered the gold standard, AI-augmented CXR presents a cost-effective, scalable option for triage in resource-constrained environments.

4.4 COVID-19 Diagnosis

AI models such as COVID-Net [25], DeepCOVID-XR [34] and CoVNet [42] have proven effective in distinguishing COVID-19 from other forms of pneumonia. Both COVID-Net and DeepCOVID-XR are specifically designed for the analysis of chest X-rays (CXR), whereas CoVNet is utilized for the detection of COVID-19 via CT scans. COVID-Net was one of the first open-source deep learning models developed for the identification of COVID-19 in chest X-rays, created by Linda Wang and Alexander Wong from the University of Waterloo. It received acclaim for its transparency and the provision of a public dataset. Despite being a groundbreaking AI model for COVID-19 detection, it had some limitations. While initial studies demonstrated substantial accuracy, its reliance on small datasets posed challenges for clinical application. Later models, such as DeepCOVID and CoVNet, improved performance by leveraging larger datasets.

V. CHALLENGES & LIMITATIONS

Computer-Aided Diagnosis (CAD) systems for chest X-rays (CXRs) offer potential but encounter several notable challenges. These challenges encompass limited and biased datasets, noise in labeling and variability in annotations, overfitting and insufficient generalizability, difficulties with the black-box nature and explainability, as well as inadequate prospective validation and regulatory obstacles (US FDA 2021a, 2021b) [28], [29]. Future research should prioritize larger datasets, explainable AI (XAI), and prospective trials to overcome these shortcomings.

VI. FUTURE TRENDS IN AI ASSISTED TECHNOLOGY

While CAD systems for CXR analysis continue to advance, there remains a critical need to develop multimodal AI-based CAD systems that integrate CXRs with electronic health records (EHR) for comprehensive diagnostics. Moreover, research should focus on federated learning (FL), a groundbreaking method for training AI models on decentralized medical data, such as CXRs from multiple hospitals, without disclosing raw patient information. The recent rise of AI-assisted PACS (Picture Archiving and Communication System) integration is helping radiologists deploy AI for real-time CXR analysis within clinical workflows, enabling prioritization of critical cases [6]. Additionally, improving robustness is essential, which involves using adversarial training to reduce false positives (FP), often caused by image artifacts (like ECG leads and motion blur), low-quality scans (such as under- or overexposure), and data bias (including overfitting to training datasets). Therefore, addressing these challenges is crucial for future research in CAD systems.

VII. CONCLUSION

AI-driven CAD systems for CXR analysis show great potential in enhancing diagnostic accuracy and accessibility, especially in resource-limited environments. However, issues such as dataset biases, model transparency, and regulatory challenges need to be addressed before widespread clinical use. Future research should focus on creating generalizable, explainable, and ethically responsible AI models to build trust and improve usability in real-world healthcare settings.

REFERENCES

[1] S. Raoof, D. Feigin, A. Sung, S. Raoof, L. Irugulpati, and E. C. Rosenow, "Interpretation of plain chest roentgenogram," *Chest*, vol. 141, no. 2, pp. 545–558, 2012, doi: 10.1378/chest.10-1302.

[2] B. Van Ginneken, B. M. Ter Haar Romeny, and M. A. Viergever, "Computer-aided diagnosis in chest radiography: A survey," *IEEE Trans. Med. Imaging*, vol. 20, no. 12, pp. 1228–1241, 2001, doi: 10.1109/42.974918.

[3] P. Rajpurkar *et al.*, "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning," *arXiv:1711.05225v3*, 2017. http://arxiv.org/abs/1711.05225.

[4] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, "ChestX-ray8: Hospital-scale chest X-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases," in *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR*, 2017, pp. 3462–3471, doi: 10.1109/CVPR.2017.369.

[5] J. Irvin *et al.*, "CheXpert: A large chest radiograph dataset with uncertainty labels and expert comparison," in *AAAI Conference on Artificial Intelligence*, 2019, pp. 590–597, doi: 10.1609/aaai.v33i01.3301590.

[6] A. Hosny, C. Parmar, J. Quackenbush, L. H. Schwartz, and H. J. W. L. Aerts, "Artificial Intelligence in Radiology," *Nat Rev Cancer*, vol. 18, no. 8, pp. 500–510, 2018, doi: 10.1038/s41568-018-0016-5.

[7] S. Kulkarni, N. Seneviratne, M. S. Baig, and A. H. A. Khan, "Artificial Intelligence in Medicine: Where Are We Now?," *Acad. Radiol.*, vol. 27, no. 1, pp. 62–70, 2019, doi: 10.1016/j.acra.2019.10.001.

[8] E. Çallı, E. Sogancioglu, B. van Ginneken, K. G. van Leeuwen, and K. Murphy, "Deep learning for chest X-ray analysis: A survey," *Med. Image Anal.*, vol. 72, 2021, doi: 10.1016/j.media.2021.102125.

[9] D. Ardila *et al.*, "End-to-end lung cancer screening with three-dimensional deep learning on low-dose chest computed tomography," *Nat. Med.*, vol. 25, no. 6, pp. 954–961, 2019, doi: 10.1038/s41591-019-0447-x.

[10] K. H. Reinert and J. H. Rodgers, "Deep learning at chest radiography: Automated Classification of Pulmonary Tuberculosis by Using Convolutional Neural Networks," *Radiology*, vol. 000, no. 0, pp. 61–98, 2017.

[11] F. Coppola *et al.*, "Artificial intelligence: radiologists' expectations and opinions gleaned from a nationwide online survey," *Radiol. Medica*, vol. 126, no. 1, pp. 63–71, 2021, doi: 10.1007/s11547-020-01205-y.

[12] Y. Erdaw and E. Tachbele, "Machine learning model applied on chest X-ray images enables automatic detection of COVID-

19 cases with high accuracy," *Int. J. Gen. Med.*, vol. 14, pp. 4923–4931, 2021, doi: 10.2147/IJGM.S325609.

[13] S. Jaeger, S. Candemir, S. Antani, Y. J. Wáng, P. Lu, and G. Thoma, "Two public chest X-ray datasets for computer-aided screening of pulmonary diseases," *Quant. Imaging Med. Surg.*, vol. 4, no. 6, pp. 475–477, 2014, doi: 10.3978/j.issn.2223-4292.2014.11.20.

[14] S. Shilaskar and A. Ghatol, "Feature selection for medical diagnosis: Evaluation for cardiovascular diseases," *Expert Syst. Appl.*, vol. 40, no. 10, pp. 4146–4153, 2013, doi: 10.1016/j.eswa.2013.01.032.

[15] S. G. Mallat, "A theory for multiresolution signal decomposition: The wavelet representation," *IEEE Trans. Pattern Anal. Mach.*, vol. II, no. 7, pp. 494–513, 1989, doi: 10.1515/9781400827268.494.

[16] I. T. Jolliffe, *Principal component Analysis, Second Edition*, vol. 20, no. PART A. 1998.

[17] Vapnik and V. N., *The Nature of Statistical Learning Theory*. 1995.

[18] L. Breiman, "RANDOM FORESTS," *Statistics Department University of California Berkeley, CA 94720*. pp. 1–33, 2001, doi: 10.14569/ijacsa.2016.070603.

[19] T. M. Cover and P. E. Hart, "Nearest Neighbor Pattern Classification," *IEEE Trans. Inf. Theory*, vol. 13, no. 1, pp. 21–27, 1967, doi: 10.1109/TIT.1967.1053964.

[20] S. L. Dawid W. Hosmer, *Applied-Logistic-Regression*. 2000.

[21] A. Esteva *et al.*, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, 2017, doi: 10.1038/nature21056.

[22] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," *arXiv:1608.06993v5*. 2018, doi: 10.1109/CVPR.2017.243.

[23] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *arXiv:1512.03385v1*, pp. 770–778, 2016, doi: 10.1109/CVPR.2016.90.

[24] M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," *arXiv:1905.11946v5*, pp. 10691–10700, 2019.

[25] L. Wang, Z. Q. Lin, and A. Wong, "COVID - Net : a tailored deep convolutional neural network design for detection of COVID - 19 cases from chest X - ray images," *Sci. Rep.*, no. 0123456789, pp. 1–12, 2020, doi: 10.1038/s41598-020-76550-z.

[26] A. Dosovitskiy *et al.*, "An Image Is Worth 16X16 Words: Transformers for Image Recognition At Scale," 2021.

[27] F. Wang *et al.*, "Residual attention network for image classification," *arXiv:1704.06904v1*. 2017, doi: 10.1109/CVPR.2017.683.

[28] US FDA, "Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD) Action Plan," no. January. pp. 4023–4024, 2021, doi: 10.1145/3447548.3470823.

[29] US FDA, "Good Machine Learning Practice for Medical Device Development: Guiding Principles," *U.S. Food and Drug Administration (FDA)*, no. October. p. 1, 2021.

[30] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization," in *Proceedings of the IEEE International Conference on Computer Vision*, 2017, pp. 618–626, doi: 10.1109/ICCV.2017.74.

[31] I. P. de Sousa, M. M. B. R. Vellasco, and E. C. da Silva, "Local interpretable model-agnostic explanations for classification of lymph node metastases," *Sensors (Switzerland)*, vol. 19, no. 13, pp. 7–9, 2019, doi: 10.3390/s19132969.

[32] Y. Nohara, K. Matsumoto, H. Soejima, and N. Nakashima, "Explanation of machine learning models using shapley additive explanation and application for real data in hospital," *arXiv:2112.11071v2*, vol. 214, no. February, pp. 1–7, 2022, doi: 10.1016/j.cmpb.2021.106584.

[33] A. P. Brady, "Error and discrepancy in radiology: inevitable or avoidable?," *Insights Imaging*, vol. 8, no. 1, pp. 171–182, 2017, doi: 10.1007/s13244-016-0534-1.

[34] P. Ramsey M. Wehbe, MD • Jiayue Sheng, BS • Shinjan Dutta, BS • Siyuan Chai • Amil Dravid • Semih Barutcu, MS • Yunan Wu, MS • Donald R. Cantrell, MD, PhD • Nicholas Xiao, MD • Bradley D. Allen, MD, MS • Gregory A. MacNealy, MD • Hatice Savas, MD • Rishi Agr, "DeepCOVID-XR: An Artificial Intelligence Algorithm to Detect COVID-19 on Chest Radiographs Trained and Tested on a Large U.S. Clinical Data Set," *Radiology*, vol. 299, pp. E167–E176, 2021, doi: https://doi.org/10.1148/radiol.2020203511.

[35] S. Horng, R. Liao, X. Wang, S. Dalal, P. Golland, and S. J. Berkowitz, "Deep learning to quantify pulmonary edema in chest radiographs," *Radiol. Artif. Intell.*, vol. 3, no. 2, 2021, doi: 10.1148/ryai.2021190228.

[36] A. Bustos, A. Pertusa, J. M. Salinas, and M. de la Iglesia-Vayá, "PadChest: A large chest x-ray image dataset with multi-label annotated reports," *Med. Image Anal.*, vol. 66, p. 101797, 2020, doi: 10.1016/j.media.2020.101797.

[37] J. P. Cohen, P. Morrison, L. Dao, K. Roth, T. Duong, and M. Ghassem, "COVID-19 Image Data Collection: Prospective Predictions are the Future," *Mach. Learn. Biomed. Imaging*, vol. 1, no. December 2020, pp. 1–38, 2020, doi: 10.59275/j.melba.2020-48g7.

[38] J. P. Cohen *et al.*, "Predicting COVID-19 Pneumonia Severity on Chest X-ray With Deep Learning," *Cureus*, vol. 12, no. 7, 2020, doi: 10.7759/cureus.9448.

[39] Z. Z. Qin *et al.*, "Tuberculosis detection from chest x-rays for triaging in a high tuberculosis-burden setting: an evaluation of five artificial intelligence algorithms," *Lancet Digit. Heal.*, vol. 3, no. 9, pp. e543–e554, 2021, doi: 10.1016/S2589-7500(21)00116-3.

[40] FIND, "Digital Chest Radiography and Computer-Aided Detection (CAD) Solutions for Tuberculosis Diagnostics: Technology Landscape Analysis," 2021.

[41] A. J. Codlin *et al.*, "Independent evaluation of 12 artificial intelligence solutions for the detection of tuberculosis," *Sci. Rep.*, vol. 11, no. 1, pp. 1–11, 2021, doi: 10.1038/s41598-021-03265-0.

[42] P. Kedia, Anjum, and R. Katarya, "CoVNet-19: A Deep Learning model for the detection and analysis of COVID-19 patients," *Appl. Soft Comput.*, vol. 104, p. 107184, 2021, doi: 10.1016/j.asoc.2021.107184.