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A Systematic Review of Recent Chest Radiograph Bone Suppression Techniques

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ABSTRACT

Chest radiograph (CXR) are essential diagnostic tools to visualize the thoracic cavity's anatomical structures, particularly the lungs. However, the interpretability of these radiographs can be compromised by the presence of overlying bones, such as the ribs and clavicles, which may obstruct the view of the lung regions. Recently, the bone suppression technique applied to CXR has shown promise in aiding radiologists and computer-aided diagnosis systems in detecting lung diseases. Numerous studies have indicated that employing bone-suppressed images (BSIs) provides clinical evidence of enhancing diagnostic accuracy and confidence. This systematic review paper provides a recent of CXR bone suppression techniques and highlights their respective results. The preference for systematic analysis over traditional literature review stems from its capability to mitigate research bias. Recently, researchers increasingly favour using deep learning methodology to suppress bone structures. Implementing these techniques opens a pathway for various applications, particularly in lung nodule detection or pathology assessment through radiological analysis of CXR.

Keywords:
Chest radiograph; Bone suppression; Image segmentation; Deep learning

1. Introduction

Lung cancer remains the predominant cause of cancer-related mortalities worldwide [1-3]. A significant challenge contributing to this grim statistic is the early detection of lung cancer nodules, significantly when they overlap with other thoracic structures in radiographic images. Chest radiographs (CXR), the frontline diagnostic tool for lung anomalies, can sometimes obscure nodules due to the overlay of bony structures like ribs and clavicles [4,5]. Therefore, enhancing nodule visibility on CXR is crucial for accurate and early detection.

Historically, dual-energy subtraction (DES) has been employed to separate bone and soft tissue images [6,7]. Still, with the exponential growth in computational power and the advent of artificial intelligence (AI), new methodologies leveraging deep learning, and particularly generative

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adversarial network (GAN), have emerged [8]. These techniques aim to suppress bone shadows, accentuating the nodules and providing a clearer picture for radiologists and clinicians [9].

Moreover, the integration of AI in medical imaging has shown potential not only in enhancing image quality but also in predictive analysis, adding a layer of precision to early diagnosis [10,11]. The incorporation of advanced algorithms in radiography also hints at a future where technology could possibly assist, if not partially replace, certain diagnostic interpretations, ensuring quicker and more accurate results [12].

This systematic review addresses critical gaps in the interpretability of CXR, which are often compromised by overlying bones such as ribs and clavicles that obscure lung regions and hinder disease detection. The review consolidates recent advancements in bone suppression techniques, particularly emphasizing the role of deep learning methodologies, which have shown promise in enhancing diagnostic accuracy and confidence. Drawing from peer-reviewed articles, we explore the underlying principles of these methods, evaluate their performance metrics, and provide insights into their real-world applicability. The ultimate goal is to offer readers a comprehensive understanding of current bone suppression techniques, guiding future research and clinical applications in chest radiography.

2. Literature Search

The literature review for this study is based on the PRISMA technique, a standard for systematic reviews, ensuring comprehensive and accurate results [13,14]. Focusing on bone suppression techniques in chest radiographs, we used two reputable databases: Web of Science and Scopus. Searches were initiated with keywords like "chest," "rib," "suppress," "radio," and "x-ray.", and primary articles' references were checked for more relevant studies.

Titles and abstracts were then carefully screened, discarding unrelated papers. Eligibility was determined by examining full texts for relevance to bone suppression, research methods, peer-reviewed publication, and significant contributions to the field. From eligible papers, data on methodologies, outcomes, and findings concerning bone suppression techniques in chest radiographs were extracted. This data was analysed to discern patterns, assess techniques' efficacy, and identify research gaps. Notably, despite the vastness of our chosen databases, there is a chance of missing some studies, and potential publication bias could influence results.

2.1 Identification

The systematic review process involves three primary steps for choosing appropriate publications for consideration. First, we identified relevant keywords and looked for similar terms by referencing glossaries, wordlists, information databases, and prior research. After consolidating these terms, we formulated search queries for the Web of Science and Scopus databases (as listed in Table 1). Consequently, we sourced 146 papers from these databases in the initial phase of our systematic review.

Table 1
The search string

Scopus	TITLE-ABS-KEY (chest* AND rib* AND suppress* AND radio* OR x-ray) AND PUBYEAR > 2018 AND PUBYEAR < 2024 AND (LIMIT-TO (PUBSTAGE, "final”)) AND (LIMIT-TO (SRCTYPE, "j”)) AND (LIMIT-TO (DOCTYPE, "ar”)) AND (LIMIT-TO (LANGUAGE, "English"))
Web of Science	TS= (chest* AND rib* AND suppress* AND (radio* OR x-ray*)) Refined by: || Publication Years: 2019-2023|| Document Types: Article || Languages: English ||

2.2 Screening

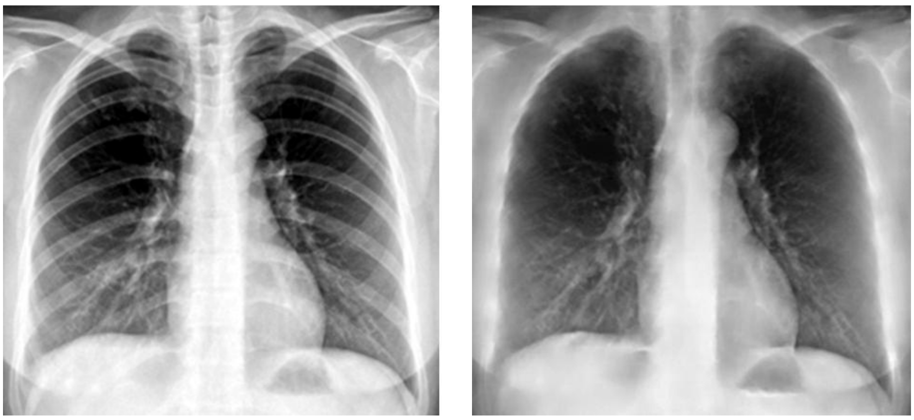
In the preliminary screening phase, duplicated papers were removed. The study's initial phase discarded 88 articles, while the subsequent phase assessed 23 papers, considering the researchers' specific inclusion and exclusion standards (refer to Table 2). Research articles, being a primary source of actionable insights, were prioritized. The scope encompassed systematic reviews, other reviews, meta-synthesis, meta-analyses, books, book series, chapters, and conference papers not featured in the recent research. The assessment only considered works written in English. Notably, this strategy was geared towards the timeframe spanning 2019 to 2023.

Table 2
The selection criterion is searching

Criterion	Inclusion	Exclusion
Language	English	Non-English
Timeline / Years	2019 – 2023	< 2019
Literature type	Journal (Article)	Conference, Book, Review
Publication Stage	Final	In Press

2.3 Eligibility

In the eligibility phase, which is the third level, 42 articles were considered. Each article's title and key content were meticulously examined during this phase to ensure alignment with the study's inclusion criteria and research goals. This led to the exclusion of 19 articles as their titles and abstracts does not have significant relevance to the objective of this study. Consequently, 23 articles were retained for further evaluation. Figure 1 depicted the sample of radiograph obtained from the retained articles.



(a) (b)

Fig. 1. Sample of chest radiograph image, (a) original and (b) predicted bone suppressed image [15]

2.4 Data Abstraction and Analysis

This research adopted an integrative analysis as a key evaluation method to explore and merge diverse research methodologies, including quantitative, qualitative, and mixed methods. The research aimed to uncover pertinent main and sub-topics. Gathering data marked the starting point for thematic evolution. As illustrated in Figure 2, the researcher delved deeply into 23 selected papers to find statements or content aligning with the research's themes. Subsequently, the researcher examined the bone suppression technique, aiming to discern and curate essential categories during the next phase. After that, critical studies on CXR bone suppression were scrutinized. The methods employed and the findings of these studies were investigated. Lastly, themes were carved out based on the gathered evidence within the scope of this research.

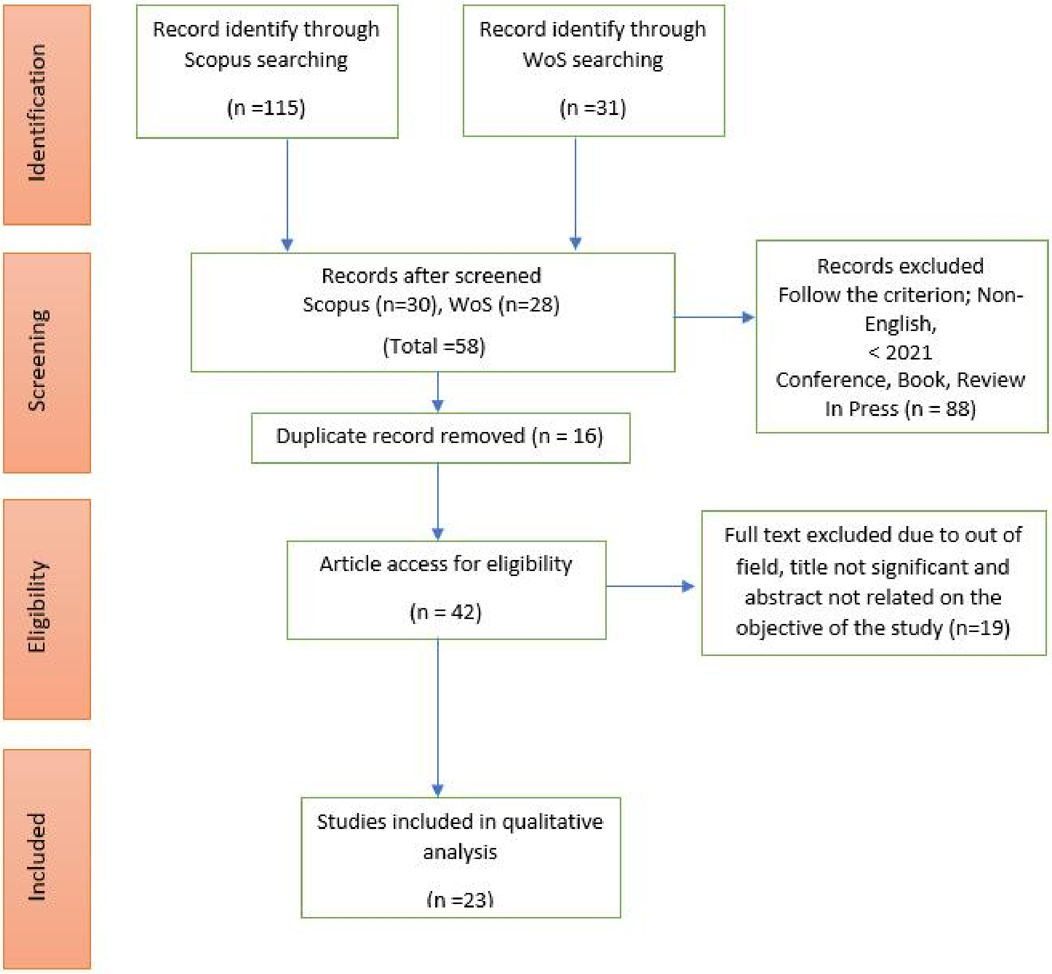


Fig. 2. Flow diagram of the proposed searching study

3. Results and Findings

Past researchers have explored numerous methodologies within the domain of CXR bone suppression. These methods have been summarized to facilitate a more straightforward comparison of the study outcomes. The summarization of these approaches and their corresponding results is presented in Table 3, offering an overview of the current state of CXR bone suppression techniques.

3.1 Clinical Relevance of Bone Suppression

Bone suppression techniques in CXR have garnered considerable attention in recent medical imaging studies. The primary objective of these methods is to refine the visibility of lung tissue by suppressing or removing the overlaying bony structures, which in turn aids in detecting subtle lung lesions and nodules. This enhanced visibility is not just a mere technological advancement; its clinical implications are profound. Several studies, including those by Zarshenas *et al.,* [16], and

Chen *et al.,* [17], vouch for bone suppression's pivotal role in elevating the clarity of lung lesions. These holds promise for enhanced diagnostic accuracy for radiologists and bolsters the reliability of computer-aided diagnosis systems.

Building on this foundation, Hong *et al.,* [18] further delved into the efficacy of bone suppression images (BSI) for detecting these subtle abnormalities. Their findings were striking. Across the board, regardless of the expertise level of the reader, the use of BSI amplified diagnostic performance. The implications were particularly evident for junior radiology residents and non-radiology clinicians. The discernible difference in their detection capabilities when using BSI underscores its potential to level the playing field, bridging the knowledge chasm between seasoned experts and those still climbing the learning curve.

3.2 Technological Strategies for Bone Suppression

Modern technological advancements have led to the development of various strategies to enhance the clarity of lung tissue obscured by overlaying bony structures. From traditional techniques like dual-energy subtraction (DES) imaging to innovative deep learning methods, this section delves into the myriads of technological solutions designed to optimize the bone suppression process, thus improving diagnostic accuracy.

3.2.1 Dual-energy subtraction (DES) imaging

A widely recognized method for bone suppression is dual-energy subtraction (DES) imaging. This technique capitalizes on the differential absorption properties of bones and soft tissues under diverse X-ray energies, facilitating the production of markedly clear soft tissue images [17,19]. Do *et al.,* studies [20] provides an enhancement to DES, wherein an automatic algorithm has been devised that precisely discerns the factors of bone and soft tissue crucial for subtraction. Integral to this innovation is the harmonization of the window/level ratio with radiographic histogram analysis.

Further enriching the understanding of radiography techniques, Takagi S. *et al.,* [21,22] have delved into the relationship between tube voltage and image quality, particularly in the context of bone-suppression. Their findings indicate that applying lower tube voltage to bone-suppressed chest radiographs not only boosts contrast and contrast-to-noise ratio (CNR), especially in regions where the lung fields overlap with ribs, but it also significantly reduces the patient's radiation exposure. More compellingly, even in areas devoid of rib overlap, bone-suppression techniques have showcased an uptick in both contrast and CNR values.

Collectively, these insights underscore the burgeoning potential of bone-suppression techniques, with a notable emphasis on the synergy between DES imaging and tube voltage adjustments. Such advancements are pivotal for the radiography domain, aligning improved imaging fidelity with patient safety considerations.

3.2.2 Deep learning approaches

In the realm of bone suppression technologies, several methodologies stand out. Essential techniques, for instance, have been highlighted by Chen *et al.,* [17], who introduced the wavelet-CCN. This cascaded convolutional network operates in the wavelet domain, specifically targeting bone structures in CXR. Complementing this, Matsubara *et al.,* [23] put forth a convolutional neural filter (CNF) with an impressive 89.2 % bone suppression rate.

The domain has also seen innovative GAN approaches. Zhou *et al.,* [24] championed using GAN, integrating it with conditional GAN that employs dilated convolutions. Following a different tangent, Rani *et al.,* [25] crafted the spatial feature and resolution maximization (SFRM) GAN, accentuating image quality and spatial feature retention. Han *et al.,* [26] further pushed the envelope with their GAN-based model, RSGAN, which leans on unpaired CT images to suppress ribs in CXR.

Pivoting to disease-specific models, Rajaraman *et al.,* [15] designed a deep-learning model that aids tuberculosis detection in CXR. A subsequent study by Rajaraman *et al.,* [27] unveiled DeBoNet, an ensemble of convolutional neural network models, demonstrating enhanced COVID-19 detection rates when trained on bone-suppressed images. Another interesting study by Bae *et al.,* [9] explored the potential of using a GAN-based deep learning technique for bone suppression compared to the traditional DES technique. The results were promising, with the GAN-based bone suppression showing comparable performance to the DES method. Both techniques were superior to standard CXR, especially when detecting nodules overlaid by bones or in the upper/middle lung zones.

The field has also witnessed specialized techniques, with Li *et al.,* [28] revealing a nuanced coarse-to-fine method that draws on structural priors from unpaired CT images for CXR bone suppression. Both Cho *et al.,* [29] and Liu *et al.,* [30] have made unique contributions; the former introduced a method centred on digitally reconstructed radiographs (DRRs) and a U-Net model for paediatric CXR, while the latter suggested a two-stage distillation learning strategy merged with a gradient correction approach for lateral CXR.

Xu *et al.,* [31] uniquely melded physical models with machine learning (ML), formulating a workflow that introduces the densely connected network, SADXNet, for rapid rib suppression. Finally, in preprocessing, Horry *et al.,* [32] devised a pipeline to debias CXR images, merging histogram equalization with CNN to reduce bone noise.

3.3 Efficacy and Advantages of Emerging Techniques

In radiology, particularly with CXR, there has been a consistent emphasis on the importance of advanced bone suppression techniques over traditional methods. Delving into specific advancements and findings, Chen *et al.,* [17] wavelet-CCN model stands out for its adaptability in processing CXR across various X-ray machines, showcasing exemplary performance metrics. Similarly, the CNF model, as reported by Matsubara *et al.,* [23], boasts a bone suppression rate. At the same time, DeBoNet's excellence was delineated in terms of PSNR and MS-SSIM by Rajaraman *et al.,* [27].

Moving towards preserving image quality, Zhou *et al.,* [24] accentuated the role of contextual data in achieving perceptual improvements. In a parallel vein, Rani *et al.*, [25] SFRM GAN adeptly balances the dual objectives of bone suppression and spatial quality preservation, ensuring images retain their inherent quality. Liu *et al.,* [30] further contributed to this arena with their method, which produces captivating soft-tissue visuals for lateral CXR, rivalling the clarity of authentic DES imaging. Beyond the techniques, there is also a significant impact on the practicalities of diagnostics.

Li *et al.*, [28] approach surpasses its unsupervised CXR bone suppression counterparts, notably reducing false-negative diagnoses among radiologists. This emphasis on improved diagnostics is echoed by Rajaraman *et al.* [15], who noted enhanced detection rates of TB-consistent findings using bone-suppressed CXR. Furthermore, their DeBoNet ensemble model demonstrated heightened sensitivity in identifying COVID-19-related abnormalities. This focus on detection accuracy is supported by the works of Xu *et al.,* [31] and Kanade and Helonde [33], who brought forward innovations reducing false positives in lung-related diagnostics and amplifying nodule visibility. In summary, it is abundantly clear that the future of bone suppression in CXR is tightly intertwined with the promises of AI, especially the capabilities of deep learning models.

3.4 Other AI Potential uses Beyond Bone Suppression

While bone suppression in CXRs has been a primary focus, as bones overlapping with soft tissues can hinder interpretation, the advancements in AI have paved the way for more diverse applications beyond just bone suppression. With the progression of deep learning, there has been a shift in how these technologies are employed in radiology. Liu Y. *et al.,* [34] not only used a fully convolutional DenseNet (FC-DenseNet) for delineating various rib structures but also highlighted the utility of such networks in improving diagnostic clarity. Moreover, Singh A. *et al.,* [35] innovatively combined elements from Deeplabv3+ and U-net, indicating that deep learning can be versatile in its application for segmenting both normal and abnormal CXRs.

Zhang D *et al.,* [36] introduced the CAMS-Net, which showcases how AI can be optimized for specific challenges, like rib segmentation in low-contrast areas. Their attention-driven modules emphasize the potential for improved segmentation and hint at how such innovations can be integrated into diverse networks.

Bosdelekidis *et al.,* [37] brought a different perspective to the table. Instead of merely suppressing bone structures, they emphasized how AI can quickly identify key bone points, assisting in lung field segmentation. Their introduction of a deformation-tolerant procedure demonstrates the expansive potential of AI in adapting to varied and complex challenges beyond conventional tasks.

Table 3
Summary of prevailing works

Author (Year)	Dataset	BS-Algorithm	Figure of Merit	Findings
Liu *et al.,* [19]	- DES CXR from Nanfang Hospital, Guangzhou, China - CXR from JSRT	- Hierarchically dense matching - Bayesian maximum a posteriori (MAP)	- RMSE	The proposed method performs better than the Locally Weighted Regression. The images produced are comparable to a real DES system only by using one chest radiograph input. The model tested on the JSRT dataset and successfully suppressed the bone structure.
Zarshenas *et al.,* [16]	DES CXR from The University of Chicago Medical Centre.	ASOFS-NNC (anatomy-specific, orientation frequency-specific deep neural network convolution) scheme	- SSIM - PSNR	The scheme has higher (t−test; P< 0.01) similarity and outperformed the state-of-the-art technique (AS MTANN) in terms of SSIM and PSNR. It maintains nodule visibility and separates bones, improving radiographic analysis.
Liu *et al.,* [34]	- DES CXR from Nanfang Hospital, Guangzhou, China - CXR from JSRT - NIH Chest X-ray14	FC-DenseNet	- Mean boundary distance (MBD) - Recall - Precision - F-measure	The FC-DenseNet-based deep learning method automatically delineates ribs and clavicles in CXRs. It outperformed other techniques, with notable precision, recall, and F-measure scores. Demonstrated robustness across multiple databases, it also aids in suppressing bone components.
Chen *et al.,* [17]	DES CXR from at Nanfang Hospital,	Cascaded convolutional	- RMAE - PSNR	Wavelet-CCN outperforming gradient-domain CamsNet. Utilizing Haar wavelet,

	Guangzhou, China.	network model in the wavelet domain (Wavelet-CCN)	- SSIM - Bone suppression ratio (BSR)	it produces high-quality soft-tissue images and has a higher average PSNR (39.4 dB) and SSIM (0.977) compared to CamsNet.
Takagi *et al.,* [21]	In house radiograph obtained using Fujifilm DR-ID 1200	- Radiograph processed using ClearRead BS software to produce BS image - Chest model and fake 12-mm nodule tested under four tube power levels of X-rays.	- Contrast - Contrast-to-Noise Ratio (CNR)	In bone-suppressed chest radiographs, dense nodules overlapping ribs have better contrast and CNR with lower tube voltage. Significant contrast difference exists between 70 kVp and 90 kVp in non-overlapping areas.
Takagi *et al.,* [22]	In house radiograph obtained using Fujifilm DR-ID 1200	- Radiograph processed using ClearRead BS software to produce BS image -Chest model and fake 12-mm tested under four entrance surface dose (ESD) conditions	- Contrast - Contrast-to-Noise Ratio (CNR)	Using the shortest exposure time and lowest tube voltage without increasing artifacts and noise can enhance bone-suppressed image quality and reduce patient dose. In non-rib overlapping areas, bone-suppression significantly improved contrast and CNR values, especially at 70 kVp, with no noticeable value decrease between ESDs of 0.3 and 0.1 mGy.
Matsubara *et al.,* [23]	- ChestX-ray8 from NIH - CXR from JSRT	Convolutional Neural Filter (CNF)	- BSR - PSNR - SSIM	CNF with six convolutional layers achieves 89.2% bone suppression accuracy. Compared to the conventional method (MTANN), the method suppresses all bone components.
Zhou *et al.,* [24]	- CXR from JSRT - DES of JSRT from Kaggle	Conditional Generative Adversarial Network (cGAN)	- PSNR - SSIM - NMSE	The cGAN framework demonstrates exceptional bone-suppressed image quality using a relatively small training set. The proposed method outperforms Auto-Encoder, Pix2Pix, Pix2Pix-wgangp, and Pix2Pix-MTdG models.
Li *et al.,* [28]	- CT volumes from LIDC-IDRI - CXR from Shenzhen hospital - Chest-14	-LoG Transformation - CycleGAN - Domain Adaptation - Histogram Match	- PSNR, - MAE - MSE - Weber Contrast	The proposed method surpasses state-of-the-art CXR bone suppression techniques (U-Net, CycleGAN, Blind Signal Separation, and DecGAN) regarding image quality and lung disease classification, reducing false-positive misdiagnoses and reading difficulty.
Bosdelekidis *et al.,* [37]	- Montgomery CXR - JSRT CXR	- The Contrast Limited Adaptive Histogram Equalization (CLAHE) - Hough Line Transform	- Jaccard similarity coefficient - Dice similarity coefficient (DSC) - Average Contour Distance	A rapid identification of bone points in the lung area aids in lung field segmentation without suppressing bone structures. The introduced method effectively handles other bone interferences, proves robust against lung deformations, and achieves a Dice similarity score of 0.92 on a benchmark dataset. Bone seed points consistently mark high-quality lung areas irrespective of shape and abnormalities.
Rajaraman *et al.,* [15]	- JSRT CXR - NIH–CC–DES CXR - Shenzhen TB CXR	- Residual network (ResNet)	- MAE - PSNR - SSIM	The proposed model (ResNet) has bone suppression and achieves a PSNR of 34.07 dB and MS-SSIM of 0.98. It

	- Montgomery TB CXR - RSNA CXR - Paediatric pneumonia CXR		- MS–SSIM	successfully suppresses bony structures in TB-related CXR datasets. Compared to other algorithm methods conducted in the study, ResNet performs best.
Rajaraman *et al.,* [27]	- COVID-19 CXR - RSNA CXR - NIH-CC-DES	- DeBoNet	- MS-SSIM - PSNR - SSIM - Mixed loss	The proposed DeBoNet outperforms most models with PSNR (36.7977±1.6207) and MS-SSIM (0.9848±0.0073). However, the FPN model utilizing the EfficientNet-B0 encoder backbone exhibited the best bone suppression performance, trailed by the FPN model using ResNet-18 and the U-Net employing ResNet-18 as the encoder backbone.
Singh *et al.,* [35]	In-house dataset produced by radiologist from Christian Medical College Vellore, India	- Combination of U-Net and Deeplab v3+ network	- DSC - Jaccard index -Pixel classification accuracy - Sensitivity - Specificity	A combined approach using Deeplabv3+ and U-net techniques offers enhanced bone segmentation in chest X-rays, including abnormal cases. Tested on a diverse dataset, this method shows superior bone detection and segmentation performance.
Rani *et al.,* [25]	- CXR from JSRT	Spatial Feature and Resolution Maximization (SFRM) GAN	- PSNR - NMSE - SSIM - Entropy - BRISQUE Score - Laplace Variance	The SFRM-GAN achieves a mean PSNR of 43.59 dB, mean NMSE of 0.00025, mean SSIM of 0.989, and mean entropy of 0.454 bits/pixel on a test set of 100 images. The model effectively balances bone suppression and information retention, improving spatial features and image quality. The combination of specific hyperparameters offers a suitable trade-off. SFRM-GAN significantly outperforms Pix2Pix STdG.
Han *et al.,* [26]	- CT volumes from LIDC-IDRI - CT volumes from 2017 and 2019 TianChi AI Competition for Healthcare - CXR from TBX11K - CXR from chest-14 - CXR from Montgomery County - CXR from Shenzhen Hospital	Rib Suppression (RS) GAN	- Weber Contrast - Learned Perceptual Image Patch Similarity (LPIPS) - PSNR - SSIM - MAE	RSGAN outperforms state-of-the-art methods U-Net DRR, U-Net Cycle, and Li *et al.,* in rib suppression, enhancing image quality. Combining CXR with rib-suppressed results improves lung disease classification and tuberculosis detection. The approach effectively retains anatomical details and eliminates rib residues, enhancing the accuracy and reliability of CXR-based diagnosis, particularly for pulmonary diseases.
Cho *et al.,* [29]	- CT dataset from seven multi-centres by the Korean obstructive lung disease cohort study (2005–2015) -CXR and CTs from	U-Net based approach	- PSNR - RMAE - SSIM	The developed bone suppression method preserves soft-tissue pixel intensity while effectively subtracting bones. Expert radiologists evaluated the efficacy of BSIs using a rating scale from 1 to 5. The achieved outcome of 3.31 ± 0.48 suggests that the BSIs exhibit consistent bone removal, albeit with

	Asian Medical Centre (AMC) dataset (2008 - 2020) - JSRT CXR			subtle remaining bone shadows.
Kanade *et al.,* [33]	- JSRT CXR - Budapest University Bone Shadow Eliminated Image dataset	Circular Window Adaptive Median Outlier (CWAMO)	- PSNR - MSR - Universal Quality Index	The proposed method for bone suppression outperforms the existing technique (ICA algorithm) in terms of PSNR, MSR, and IQI. For segmentation, the proposed method (active shape modelling) shows improvement in nodule area contrast of 3.83% and 23.94% shadow compared to Budapest University's Bone Shadow Eliminated Image dataset.
Horry *et al.,* [32]	- CXR from JSRT - CXR subset from LIDC	CNN-based approach	The metrics for bone suppression are not mentioned	The authors conducted experiments involving three operators: Segmentation, Cropping, and Rib Suppression. Combining all these operators yielded the most favourable outcome, achieving a consistent 80 % AUC for the JSRT - trained model. They subsequently evaluated this model on the LIDC dataset and achieved a classification accuracy of 89 %.
Xu *et al.,* [31]	- VinDr-RibCXR - NODE21 - ChestX-ray14 Benchmark dataset contributed by authors: FX-RRCXR	- SADXNet - ST smoothing	RMSE	SADXNet was trained on FX-RRCXR. It effectively maintained its ability to suppress rib structures when applied to scans from NODE21 and ChestX-ray14 datasets. SADXNet obtains a test RMSE of 2.32 ± 0.13 × 10^ (-5). In contrast to the time-intensive ST-smoothing algorithm, SADXNet suppresses a single scan in less than 1 second.
Do *et al.,* [20]	- In house dataset produced by radiologist - DE Healthcare - Fujifilm	- DES - Window/level ratio - Radiographic histogram analysis	- Runtime - Image quality comparison	The proposed algorithm achieves a runtime of 200 ms, significantly shorter than the 4-second runtime of the GE algorithm. Plus, its iterative DES process takes 6.066 seconds, outperforming the 10-second runtime of the Fujifilm algorithm. It maintains comparable image quality to other algorithms for visualizing nodules within soft tissue images.
Zhang *et al.,* [36]	- RCS-CXR - VinDr-RibCXR - JSRT CXR - Shenzhen - NIH	- CAMS-Net	- DSC - Recall - Precision - Jaccard - Accuracy	CAMS-Net, an attention-guided algorithm, improves rib segmentation in chest X-rays, particularly in low contrast and abnormal grey areas. It outperforms existing methods in tests, proving effective across multiple datasets, and its components can be adapted into other networks.
Liu *et al.,* [30]	- Lateral CXR with DES from Nanfang Hospital, Guangzhou, China	MsDd-MAP framework	- RMAE - PSNR - SSIM	The suggested technique outperforms other methods (CamsNet, Dilated CGAN, Pix2pix-STdG) through quantitative metrics and evaluation by experienced

	radiologists. The distillate model generates visually appealing soft-tissue images, showcasing its potential for resembling really dual-energy Subtraction imaging in lateral CXR.

4. Discussion and Conclusion

The ongoing advancements in CXR, specifically within bone suppression techniques, showcase a fusion of traditional approaches and modern AI solutions. Given the significant global impact of lung cancer, refining diagnostic tools to detect early-stage nodules accurately is essential. According to Takaki *et al.,* [38], employing the bone suppression technique resulted in notable enhancements in the collective figure-of-merit metrics for all radiologists, thus being advantageous in identifying subtle pulmonary lesions in digital CXR. While traditional methods like DES imaging have held their ground, the rise in AI technologies, particularly deep learning, offers innovative methods that promise enhanced diagnostic capabilities.

Modern models such as the wavelet-CCN, CNF, and various GAN strategies present clear benefits, offering high-resolution imaging despite the challenges posed by overlapping bony structures in the chest. Their ability to adapt to different X-ray machines and maintain image quality makes them invaluable in contemporary medical diagnostics. More than just technological advancements, these methods present substantial clinical benefits. Improved diagnostic accuracy, reduced instances of overlooked conditions, and increased detection rates for diseases like tuberculosis and COVID-19 underscore the importance of these advancements.

Recent works emphasize the integration of AI into the radiology workflow. Dikici *et al.,* [39] chart the progression of AI from mere visualization to feedback-driven retraining in radiological tasks. Ranschaert *et al.,* [40] spotlight AI's prowess in optimizing nondiagnostic operations, while Sohn *et al.,* [41] address integration challenges by proposing an adaptable open-source framework. In essence, the prevailing literature indicates that AI and ML are set to be pillars in modern radiology by elevating diagnostic precision and operational efficiency.

However, the swift assimilation of AI into radiology demands substantial revamps in radiologist and technician training. Schuur *et al.,* [42] note the superficial nature of most current AI training, which mainly introduces fundamental concepts in brief modules. Richardson *et al.,* [43] stress that radiologists must grasp core AI tenets, primarily when overseeing AI system management. Yang *et al.,* [44] reveal that while the impact of AI on radiology is anticipated, a complete replacement of radiologists is still possible. A cohesive approach between AI specialists and radiologists is universally advocated. The core is for AI to revolutionize radiology; thorough training and a symbiotic alliance between the IT and medical sectors are pivotal.

While the potential of AI techniques appears promising, it is essential to understand their pitfalls for the images they generate thoroughly. For instance, the initial enthusiasm surrounding AI in medical imaging was tempered by scepticism due to concerns about overfitting, data bias, and generalizability [45-47]. The reviewed articles show it leans heavily on the Posterior-Anterior (PA) projection as their training data, frequently neglecting other projections like Anterior-Posterior (AP) and lateral views, including paediatric patients. Relying predominantly on PA-trained AI models can create challenges when applied to diverse clinical contexts. The absence of direct comparative research between DES and AI-based approach further fuels hesitancy towards embracing AI-centric techniques.

The medical community has also expressed concerns regarding the ethical implications of relying heavily on automated systems, emphasizing the importance of human oversight in diagnostic processes [48-50]. Reliance on automated AI can raise concerns about accountability. Determining responsibility becomes complex when misdiagnoses occur due to AI errors. Should the liability reside with the software developers, the medical practitioners who placed their confidence in it, or the institutions that implemented it? These ethical grey areas necessitate clear guidelines and protocols to ensure patient safety and care remain paramount.

Moreover, assessing and comparing AI performance is challenging due to inconsistencies in image quality assessment measures across reviewed studies. While some studies utilize objective numerical metrics such as mean absolute error (MAE), peak signal-to-noise ratio (PSNR), structural similarity (SSIM), and bone suppression ratio (BSR), these metrics can differ from one study to another. Because of this absence of standardization, some research relies on physicians' subjective evaluations of image quality [51].

Nevertheless, it is crucial to interpret these findings with a critical mindset. Every technique presents unique challenges, and the potential for bias in published research should be addressed. As AI and deep learning gain traction in CXR, continuous research, rigorous validation, and harmonious integration of novel and conventional methodologies are essential. In summary, the present literature signals a trend where AI-powered bone suppression techniques, backed by solid research, are set to play a crucial role in chest imaging. As technology and clinical needs evolve, researchers and clinicians will benefit from collaborative efforts, ensuring that the best of traditional and modern approaches are brought to the forefront of medical diagnostics.

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