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Utility of bone suppression imaging for the detection of pneumonia on chest radiographs

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ABSTRACT

Introduction: Chest X-rays (CXR) are routinely used to diagnose lung and heart conditions. AI based Bone suppression imaging (BSI) aims to enhance accuracy in identifying chest anomalies by eliminating bony structures such as the ribs, clavicles, and scapula from CXRs. The aim of this retrospective study was to assess the clinical value of BSI in detecting pneumonia.
Methods: Ninety-nine emergency patients with suspected pneumonia underwent erect postero-anterior CXRs. The BSI processing system was used to generate corresponding bone-suppressed images for the 99 radiographs. Each patient had undergone a computed tomography (CT) examination within 48 h, considered the standard of reference. Two blinded readers separately analyzed images, indicating confidence levels regarding signs of pneumonia for each lung separated in three fields, first with standard images, then with BSI. Sensitivity, specificity, predictive values, and readers' certitude were calculated, and inter-reader agreement was evaluated with the kappa statistic.
Results: Out of the 99 included cases, 39 cases of pneumonia were diagnosed (39.4%). Of the remaining 60 patients, 14 presented only pleural effusions (14.1%). BSI images led to a significant increase in false positives (+251%) and significantly affected one reader's diagnosis and certitude, decreasing accuracy (up to 17%) and specificity (up to 14%). Sensitivity increased by 66% with BSI. Inter-reader agreement ranged from weak to moderate (0.113–0.53) and did not improve with BSI. For both readers, BSI images were read with significantly lesser certitude than standard images.
Conclusion: BSI did not add clinical value in pneumonia detection on CXR due to a significant increase in false positive results and a decrease one readers' certitude.
Implication for practice: The study emphasizes the importance of proper clinical training before implementing new post-processing and artificial intelligence (AI) tools in clinical practice.

Introduction

In radiology, conventional chest X-rays (CXRs) are still the most frequently performed images worldwide and the initial technique of choice to diagnose various lung and heart conditions in the emergency room (ER) department.[1] They represent 52% of x-rays performed annually in the ER department of the study's context, a large university teaching hospital in Switzerland. However, for this region, most often only one projection is performed: the frontal one. This implies that bony structures such as the ribs, clavicles and scapula overlap with the pulmonary tissue and can obscure important pathology like pulmonary nodules, masses, or infiltrates.[2,3] To address this issue, various imaging techniques have been developed to help allow a more clear interpretation of the

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lungs on CXRs.[4] These techniques are either based on artificial intelligence (AI) or technological equipment improvements.[4–6] Bone suppression imaging (BSI) is a post-processing technique using AI algorithms to remove bones from CXRs images. It has been considered by some as a valuable tool for improving the quality and diagnostic accuracy of CXRs in radiology.[6–9] However, the technique is not commonly implemented in practice, even though literature has shown a gain in its popularity in recent years thanks to its potential to reduce the need for more invasive procedures, that also need higher doses, such as chest computed tomography (CT).[10] One advantage of BSI is that it differs from other subtraction techniques used in radiography, such as the dual-energy technique, which uses two different X-ray energies to differentiate bone from soft tissue, as it does not need other equipment nor increase patient dose.[6–9]

The technique has been shown to be a more practical and efficient option for improving CXR's quality, with the added benefit of improved detection of small lung nodules compared to dual-energy radiography. Several studies have demonstrated the effectiveness of BSI in improving the detection of pulmonary nodules in CXR, with an increase in specificity ranging from 66% to 71%, and an increase of lung cancer sensitivity of approximately 6%.[9,11] Another study emphasized the increase in sensitivity thanks to the technic, especially when nodules overlap with bone matter.[12] It has also been shown that diagnostic accuracy was significantly improved when BSI images were used in conjunction with standard CXRs in the case of focal pneumonia detection.[13]

However, it is important to note that the use of AI techniques in radiology may bring both opportunities and challenges. Many studies have shown significant concern on the level of AI literacy and limited management experience among healthcare professionals, which can contribute to fears about AI implementation, such as the “black box” effect and its potential to generate false pathologies that might impact patient outcomes.[14–16]

According to a recent study, successful AI integration requires developing technical skills and enhancing knowledge.[16] AI solutions must be explainable, interpretable, and integrated into workflows. Familiarity with AI images is crucial for building confidence and competence of clinicians. The same authors emphasize the need for a well-planned implementation strategy that meets the needs of healthcare professionals and supports the transition to AI-enhanced clinical practice. Involving healthcare professionals with practical, context-specific examples is key to overcoming certain barriers like a lack of understanding. Inadequate training can lead to resistance and errors.[16]

To the best of our knowledge, no recent studies have assessed the diagnostic value of BSI in detecting pneumonia as distinctive pathology in the emergency room (ER) context. This retrospective study aimed to determine the added value of BSI in detecting pneumonia within the framework of routine clinical practice in the ER setting.

Material & methods

Context

This study was conducted in Lausanne University Hospital, in Switzerland. Approval for the study was obtained from the state's ethics committee (Ref: 2022-01913). Informed general patient consent was obtained using a comprehensive information sheet.

The study included adult patients (≥18 years old) referred from the ER to the radiology department for an erect PA CXR, paired with a CT performed within a 48-h window requested by clinicians based on patient's symptoms, between May and October 2021. The sample size was directly limited by the duration for which the software was available for testing in the radiology department. Since CT provides higher sensitivity and specificity in pulmonary pathology detection, it was used as the benchmark for accuracy in this study.[3] Exclusion criteria related to image quality included motion artifacts or insufficient inspiration, excessive metallic artifacts on CT, truncated lung fields, and incorrect patient positioning for radiography. An experienced radiographer assessed the image quality of both the radiographs and the CT images to categorize cases for inclusion. All CXRs were acquired using a Phillips' C90 digital x-ray device and post-processing of images was applied according to the manufacturer's recommendation.

Subjective analysis

Two readers (reader 1 and reader 2) with four years experience in chest imaging, respectively, and blinded to any clinical results separately analyzed the CXRs of all patients on a picture archiving and communication system workstation (PACS; Carestream Vue, v. 11.4; Carestream Health, Rochester, NY). First, both readers underwent a brief training by reading five cases to become familiar with BSI images. This training involved five patients who were not part of the observer study. The cases included examples with and without focal pneumonia. During the training, the correct diagnosis was provided only after each case was completed. During the study, the readers reviewed each image set separately, with a one-month interval to minimize recall bias and remained blinded to any clinical and radiological information. They read standard CXRs of each included patient and, after one month, they read the corresponding BSI images, without comparing to original CXR images. Six different regions were selected in each CXR for statistical data collection: upper, mid, and lower pulmonary field, for both sides. Each region was individually analyzed for pulmonary ill-defined opacities with or without air bronchogram, indicating potential underlying pneumonia (yes = 1, no = 0). Observers quantified their certitude level using three intervals ranging from 60% to 100%; where 60% corresponded to “likely”, 80% to “very likely”, and 100% to “certain”, similar to methods used in other observer studies.[17,18] Moreover, the two observers determined the presence of pleural effusion.

Chest CT images of each included patient were evaluated separately by a third radiologist (reader 3) with >20 years of experience in chest imaging in view of signs of pneumonia.

Readings were collected and managed using REDCap (Research Electronic Data Capture) electronic data capture tool hosted by the institution.

Statistics

Demographic patient data was assessed using descriptive statistics (mean, standard deviation, and median).

Contingency tables were established to compute the sensitivity and specificity as well as the negative and positive predictive values for each radiologist at each lung field, both before and after the application of the BSI, in comparison to the gold standard (CT). To assess the accuracy between the evaluation obtained from the images acquired with or without BSI with respect to the correspondent CT examination the non-parametric McNemar's test for paired samples was conducted. The Fisher exact test was used for determining significant differences within confusion matrices. For all statistical analyses, significance level was fixed at $p < 0.05$ and all the p-values were adjusted using the False Discovery Rate (FDR) methods to correct for multiple comparisons.

Using the kappa statistics according to Landis and Koch (1977), inter-observer agreement was determined as follows: kappa = 0–0.2 was interpreted as “very weak agreement,

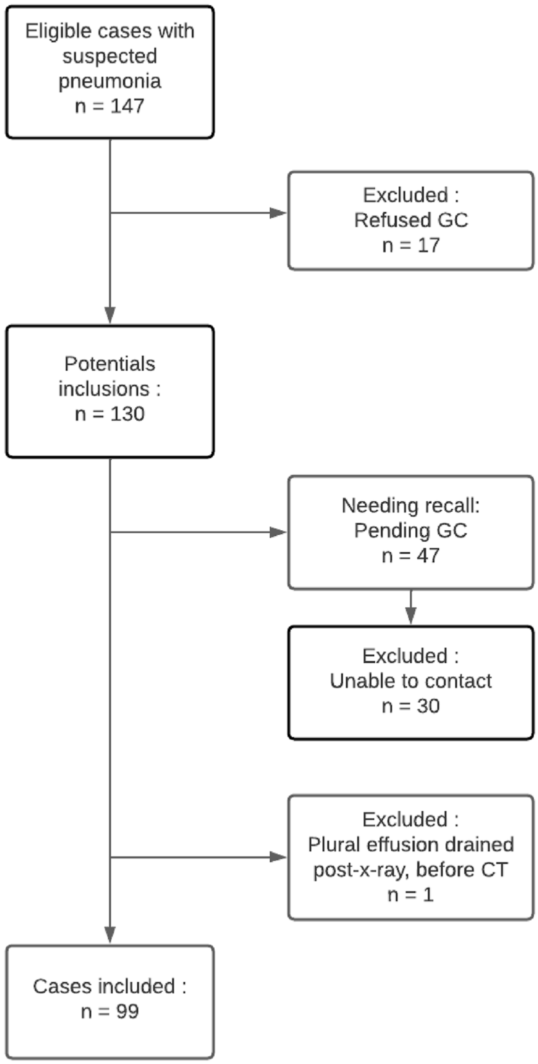

Figure 1. Patient case inclusion flow chart. GC = general consent.

Table 1
Number and percentage variability of true-positives (TP), true-negatives (TN), false-positives (FP), and false-negatives (FN) with and without BSI for both readers and all regions combined.

	TP	TN	FP	FN
Without BSI (N = 1188)	95 (8%)	955 (80.4%)	39 (3.3%)	99 (8.3%)
With BSI (N = 1188)	120 (10.1%)	857 (72.1%)	137 (11.6%)	74 (6.2%)
% difference	+26%*	−10%*	+251%*	−25%*

*Significant difference ($p < 0.05$).

kappa = 0.21–0.4 as "weak agreement", kappa = 0.41–0.6 as "moderate agreement", kappa = 0.61–0.8 as "important agreement", and kappa 0.81–1.00 as "near perfect agreement".[19]

All the statistical analyses were performed using RStudio Team (2022) software version 2022.12.0 Build 353.

Results

Sample size and patient demographics

Eligible cases, meaning patients who met the inclusion criteria during the timeframe, comprised 147 patients. A sample of 99 patients (42.4% women, n = 42, mean age = 64.3 ± 17, n = 99) were included in the study after obtaining general consent (Fig. 1). In 39 cases (39.4%), signs of pneumonia were identified on the CT images. Pleural effusions were identified in 31 cases (31.3%) and among these cases, 14 patients (14.1%) presented no other pathology beside pleural effusion. The remaining 46 patients (46.5%) showed no pathology. No examination was excluded for suboptimal quality in this study.

Contingency tables

Contingency tables were established for each reader and each of the six lung fields. After summing the data, Table 1 shows that the number of false positives (FP) results increased significantly for each region with the use of BSI (+251%) (Fig. 2). Indeed, for both readers and for all six lung fields combined there were 39 FP cases without BSI (3.3%), compared to 137 with BSI (11.6%). Statistical analysis showed that these differences were significant (Odds ratio = 0.461, $p < 0.001$). The number of true positives (TP) results also slightly increased (+26%) (Fig. 3).

CXR reading per reader without/with BSI versus gold standard (CT)

Statistical differences in the reporting of pneumonia or ill-defined opacities by radiologists were determined before and after BSI ($p < 0.05$) in comparison to the gold standard CT.

Concerning pneumonia detection, for reader 1, two of the six pulmonary fields showed significant differences between images without BSI and the gold standard. Furthermore, for the same reader, significant differences between BSI images and the gold standard were found in three out of the six pulmonary fields. These differences were observed in both upper lung fields and the lower right lung field. For reader 2, no significant differences were found.

Concerning the detection of left pleural effusion, reader 1 and 2 showed significant differences between BSI and the gold standard.

Table 2
Accuracy, specificity, sensitivity, PPV, and NPV with and without BSI, according to region and reader.

Region	Accuracy [%]		Specificity [%]		Sensitivity [%]		NPV [%]		PPV [%]	
	Reader 1	Reader 2	Reader 1	Reader 2	Reader 1	Reader 2	Reader 1	Reader 2	Reader 1	Reader 2
Left lung										
Upper	94/82*	99/94	98/84*	100/99	33/50*	83/17	96/96*	99/95	50/16*	100/50
Mid	91/83*	95/92	97/84*	100/97	45/73*	55/55	93/96*	95/94	63/36*	100/67
Lower	80/71*	84/83	88/67*	88/91	52/83*	70/57	86/93*	91/87	57/43*	64/65
Right lung										
Upper	88/73*	92/92	97/72*	99/100	25/75*	42/33	90/95*	92/92	50/28*	83/100
Mid	88/83*	90/90	100/87*	96/96	29/69*	59/59	87/92*	92/92	100/50*	77/77
Lower	77/64*	84/82	97/65*	90/87	25/61*	68/68	77/81*	88/87	78/40*	73/68

Without BSI/BSI.
*Significant difference with or without BSI ($p < 0.05$).

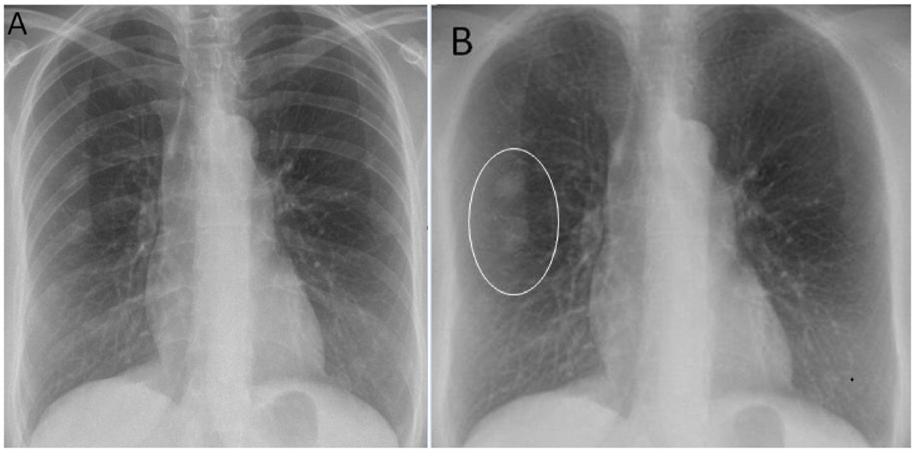

Figure 2. False-positive example. The CXR without BSI (A) was considered normal. But the CXR with BSI (B) showed ill-defined nodular opacities (B, white circle) in the right upper lung field taken for infectious lesions by the two readers. However, they corresponded to consolidated old rib fractures, as shown by CT and according to the standard CXR.

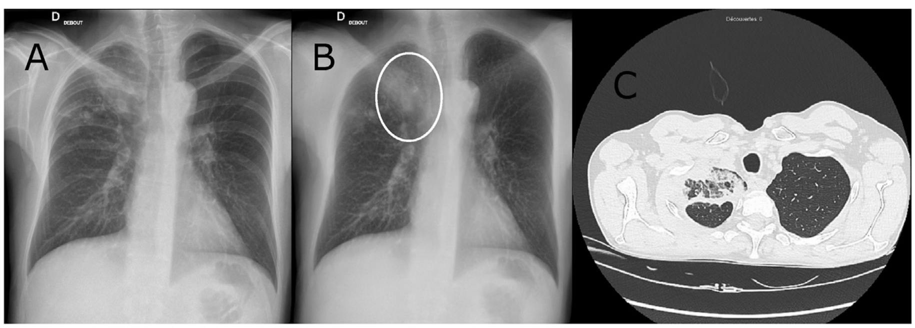

Figure 3. True-positive example. The CXR without BSI (A) showed very well-defined opacities in upper right lung field suggesting a chronic origin; however, the analysis is hampered by the superimposition of the right clavicle. The CXR with BSI (B) clearly showed an ill-defined opacity (B, white circle) in the right upper lung field which is not overlapped with the clavicle anymore. Finally, CT confirmed the presence of acute pneumonia (C).

Accuracy, sensitivity, specificity, PPV, and NPV of each reader without/with BSI (Table 2)

When comparing the first reader's reporting to the gold standard, accuracy ranged from 77% to 94% without BSI and from 64% to 83% with BSI, thus showing less accuracy when reading BSI images. Specificity ranged from 97% to 100% without BSI and from 65% to 87% with BSI. Sensitivity ranged from 25% to 52% without BSI and increased from 50% to 83% with BSI. Positive predictive values ranged from 50% to 100% without BSI and from 16% to 50% with BSI. Negative predictive values ranged from 77% to 96% without BSI and from 81% to 96% with BSI. When comparing contingency matrices, all these differences were found to be statistically significant for this reader ($p < 0.05$) (Table 2).

Similar results were found when looking at data from reader 2, however without statistical significance ($p > 0.05$). When compared with the gold standard, reader 2 achieved an accuracy between 84% and 99% without BSI, and between 82% and 94% with BSI. The specificity for reader 2 ranged from 90% to 100% without BSI, and from 87% to 100% with BSI. Sensitivity for reader 2 varied from 42% to 83% without BSI, and from 17% to 68% with. Positive predictive values for reader 2 ranged from 64% to 100% without BSI, and from 50% to 100% with BSI. Negative predictive values for reader 2 varied from 77% to 96% without BSI, and from 81% to 96% with BSI.

Table 3
Readers' certitude according to region, with or without BSI.

Region/certitude level (%)	60%	80%	100%
Left lung			
Upper (N = 198)	0/10*	3/13*	195/175*
Mid (N = 198)	1/5*	2/15*	195/178*
Lower (N = 198)	11/11	35/45	152/142
Right lung			
Upper (n = 198)	2/11*	3/21*	193/166*
Mid (n = 198)	4/5*	6/20*	188/173*
Lower (n = 198)	7/10	15/42	176/146

Without BSI/BSI.
*Significant difference with or without BSI ($p < 0.05$).

Readers' certitude

Table 3 shows all certitude levels with and without BSI according to each investigated region for both readers combined. Results show that the highest certitude, i.e., the region with the most 100% certitudes values in the evaluations, was found in the upper and mid left field without BSI (195/199 cases). The lowest, containing the least amount of 100% certitude values, was found in the lower left field with BSI (142/199 cases), followed by the lower right field with BSI (146/199 cases). For both readers combined, significant differences of certitude between reading with BSI compared to reading without BSI were found for all regions except the lower left lung, showing that images with BSI induced a significant decrease in certitude compared to the images acquired without bone suppression.

Results showed that the presence or not of pleural effusion did not have any statistical impact on sensitivity or certitude in this study.

Interobserver agreement before and after BSI

When reading CXRs without BSI, inter-reader agreement (Kappa) between the two radiologists ranged from very weak to moderate (0.113–0.53) and there was no change when reading CXRs with BSI (0.155–0.444).

Discussion

In this study, the use of Bone Suppression Imaging (BSI) did not result in any improvement in readers' accuracy for detecting pneumonia in erect chest X-rays (CXRs). Data showed a significant increase in false positives (FP) results (+251%) across all explored regions. These findings align with other studies reporting an increase in false positive results when using BSI, suggesting that BSI may lead to an elevated risk of false alarms, potentially necessitating further evaluation or follow-up tests, such as chest CT.[10,13] However, the number of true positives (TP) also increased by 26% with BSI, indicating its potential to aid in detecting pathological conditions. One reader showed a significant decrease in diagnostic certitude when using BSI, which was notably different from the other reader, possibly due to insufficient training or lack of familiarity with this type of image processing. This observation is consistent with Schalekamp et al. (2016), where a decrease in confidence was also noted when using BSI for pneumonia or infiltrates.[10] The high number of false positives in this study may be explained by significant differences shown by one reader, including a decrease in accuracy and specificity and an increase in sensitivity when reading BSI images. This may be due to the increased visibility of bronchovascular markings on BSI images, potentially inducing errors.

When compared with CT, our gold standard, this study showed no statistically significant additional value in the detection of pneumonia with BSI, regardless of the region. This contrasts with literature suggesting better detection of focal pulmonary pathologies, such as nodules.[6,10,16,20] For instance, a similar study in 2012 found that incorporating BSI with standard CXRs significantly improved diagnostic accuracy, with the area under the ROC curves increasing from 0.844 with standard CXRs alone to 0.880 with the addition of BSI images.[13] Our data also suggest that readers' confidence can vary based on the specific areas they are observing, particularly in the lower pulmonary fields, where a consistent drop in confidence was observed. This drop in confidence might be explained by the presence of the heart or pleural effusions in these regions. Additionally, we found relatively low agreement between the two readers. The noticeable decrease in confidence and accuracy when reading BSI images may also be due to radiologists not being accustomed to these types of images, leading to hesitation in fully relying on their interpretations. The evidence of improved consistency in interpretation with proper training has been highlighted in the literature, suggesting that adapting to new processing techniques might overshadow diagnostic expertise, potentially leading to a decrease in confidence and impacting diagnostic accuracy.[21–22] Furthermore, these findings may differ from other studies, as our study exclusively focused on BSI images during the second reading, rather than evaluating both the BSI and standard CXR images together.

Limitations

As a retrospective study, limitations include finite number of eligible cases due to the 48-h window for chest CT. Additionally, the number of readers (radiologists) for the study may be considered low and limit extrapolation of the results. Furthermore, the lack of the two reader's experience with the technique of BSI may have influenced our results. However, the study aimed to reproduce conditions that reflect the ER clinical routine context, which means that radiologists may not yet be familiar with certain new AI-techniques.

Furthermore, even though one month interval between reading may notably decrease recall biases, it might be insufficient to fully eliminate recall bias, especially if the patient has anatomical or pathological peculiarities, or a specific medical device that could make the case more memorable and influence future diagnostic evaluations.

This study showed very weak to moderate inter-reader agreement (Kappa) between the two radiologists for standard CXRs. However, similar scores were found in other studies involving CXRs.[23,24]

Needed implications and actions

The disparity between the studies underscores the necessity for additional research to clarify the factors impacting the efficacy of BSI in pneumonia detection. Further investigation is required to address issues surrounding reader confidence and inter-reader reliability.

The study's findings have implications for the integration of BSI into clinical practice, emphasizing the need for robust training and adaptation in BSI image interpretation. To address the potential risks of false alarms, further research is recommended to determine the specific use of BSI. These insights can guide the development of specific training programs and contribute to the responsible implementation of BSI in routine ER clinical settings.

Another approach could involve bringing in an expert with specialized AI knowledge to guide the adoption of these new programs. For this to succeed, it is crucial for management to support AI awareness initiatives and foster the development of interdisciplinary skills through both top-down and bottom-up strategies. If this is not addressed, this may induce more uncertainty, increased stress, disturb proper workflow, and potentially increase diagnostic error and thus patient outcomes.[14–16]

Conclusion

This study showed no added clinical value when considering the balance of benefits and risks associated with the use of BSI, and it revealed a significant increase in false positives in the context of pneumonia with its use. One reader had significant decrease in accuracy and certitude when using the tool. Further studies are needed to generalize these finding by including more readers and more data. However, the data encourages the need for accurate training and guidance when implementing new AI technologies within clinical setting.

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Conflict of interest statement

No conflicts of interest to disclose.

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