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Comparison of Projection and Reconstruction Techniques in Sinograms for Breast Lesion Classification

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Abstract. Breast cancer remains one of the leading causes of mortality among women worldwide, andearly detection and accurate staging of breast lesions are critical for effective treatment. Digital Breast Tomosynthesis (DBT) has emerged as a promising imaging technique, offering clearer, more layered breast images than conventional mammography. DBT generates sinograms from thin-layer projections, which are then used to reconstruct three-dimensional images. However, the reconstruction process can introduce artifacts, potentially leading to information loss and inaccuracies in lesion detection. This study compares the efficacy of direct analysis of preprocessed sinograms versus reconstructedimages for breast lesion detection using Convolutional Neural Networks (CNNs). Specifically, we evaluated sinograms from 180- degree projections versus those from 360-degree projections and reconstructed images using simpleback projection. The results demonstrate that 180-degree sinograms, when preprocessed for contrast enhancement, significantly outperform 360-degree sinograms and reconstructed images in terms of accuracy, recall, and F1 score. The superior performance of 180-degree sinograms underscores their potential as a viable alternative to traditional image reconstruction methods, offering a more effective approach to lesion detection and classification. This study contributesto advancing breast cancer diagnosis byhighlighting the advantages of using preprocessedsinograms. It suggests further exploration ofadvanced image processing techniques and neural network architectures to improve diagnosticaccuracy.

Keywords. Sinograms, DBT, detection, classification, CNN, breast lesions, image reconstruction, imaging, and projections.

1 Introduction

Breast cancer remains one of the leading causes of mortality among women worldwide. The effectiveness of treatment is highly dependent on early detection and accurate staging of breast lesions [1]. Digital Breast Tomosynthesis (DBT) has emerged as a promising technique in diagnostic imaging, providing a significant advantage over conventional mammography by offering clearer and more layered images of the breast [2]. DBT produces sinograms from thin-layer projections of the region of interest, which are combined to generate two-dimensional images containing X-ray information from various angles. These sinograms are then used to reconstruct three-dimensional images using computational algorithms [3].

However, the process of reconstructing images from sinograms can introduce artifacts, potentially leading to loss of information due to interpolation steps, suboptimal statistical weighting, shading, and other factors [4]. This loss can cause inaccuracies in lesion detection and localization. Sinograms provide detailed and distributed information throughout the projection data, enabling lesion detection and localization while improving image quality by assessing noise and spatial resolution, thereby reducing potential diagnostic errors [4].

In previous research, a methodology was proposed that leverages Convolutional Neural Networks (CNNs) to analyze DBT sinograms directly, avoiding the reconstruction process to retain maximum diagnostic information. This approach yielded promising results, with ResNet50 and ResNet18 models achieving high accuracy, recall, and F1 score [5]. The parameters of the CNN models used (ResNet50, ResNet18, AlexNet, MobileNet, and InceptionV3), along with the specifications of the computing equipment and a detailed description of the database, can be found in the previous article [5], as no changes have been made to these aspects in the current study.

This study extends previous work by integrating advanced image enhancement techniques and evaluating CNN-based models. The hypothesis is that sinograms processed with these methods, particularly those covering a 180-degree projection range, can improve breast lesion detection and classification, offering a viable alternative to traditional image reconstruction. This article contributes to the advancement of breast lesion detection and classification using DBT sinograms and CNNs, potentially improving the accuracy of breast cancer diagnosis and treatment.

2 Antecedents

Medical image analysis using sinograms has been widely explored in various domains, such as computed tomography (CT) and positron emission tomography (PET), where Convolutional Neural Networks (CNNs) and other deep learning models have shown promising results. In 2018, a study introduced the 'Machine Friendly Machine Learning' approach, utilizing CT sinograms to train machine learning models, achieving 97.5% accuracy in pathology detection, which was comparable to traditional methods based on reconstructed images [6]. A year later, in 2019, a method based on deep neural networks was presented to enhance CT lung nodule detection through sinogram space analysis, achieving an AUC of 91% and significantly outperforming existing approaches in terms of sensitivity and accuracy [7].

Despite these advances, sinogram analysis in digital breast tomosynthesis (DBT) remains an underexplored area, particularly in thedetection of breast lesions. In a previous investigation, a methodology using CNNs for lesion classification from DBT sinograms was proposed, achieving a remarkable accuracy of 94.96% with ResNet50 models. This approach proved to be aneffective alternative to traditional image reconstruction methods [5].

The literature also underscores the importance of preprocessing techniques, such as noise reduction and contrast enhancement, to improve the quality of sinogram data for analysis. In 2017, a method was proposed to enhance low-dose CT images using maximum a posteriori (MAP) estimation in sinogram preprocessing, which demonstrated an improvement in image quality compared to previous methods [8]. In 2018, superresolution techniques were employed to enhance the quality of PET scans from sinograms, highlighting the potential for more efficient and cost-effective PET systems [9].

Subsequently, in 2019, a deep learning framework was introduced to reconstruct PET images directly from sinograms, prioritizing reconstruction quality and speed, and achieving superior performance in image quality, speed, and robustness compared to traditional methods [10]. In 2020, a neural network was developed that allowed the reconstruction of high-quality PET images from sinograms, generating images with fewer artifacts and at a higher speed than conventional methods. Additionally, a study in the same year revealed that full-dose PET images generated from low-dose sinograms presented better quality and lower variation in SUV values compared to those generated in image space [11, 12].

In 2021, brain PET/CT data were used to create low-dose (LD) and full-dose (FD) sinograms, which were then used to generate FD images from LD sinograms using neural networks. This sinogram space-based method produced higher-quality images and lower bias compared to the image space-based method [13]. A parallel study compared a sinogram-based image reconstruction algorithm (DLIR) with ASIR-V in abdominal computed tomography, highlighting that DLIR outperformed ASIR-V, particularly in image quality, noise reduction, contrast, and sharpness [14].

Finally, in 2022, a PET reconstruction method using deep learning from sinograms in a long axial field of view was introduced, which improved image quality and reduced reconstruction time without the need for additional CT images. In 2023, an automated process was developed to detect and classify intracranial hemorrhages directly from sinograms using deep learning techniques. This approach achieved 94% accuracy, eliminating the need for image reconstruction and improving both diagnostic accuracy and robustness [15,16].

This study aims to extend previous work by integrating advanced image enhancement

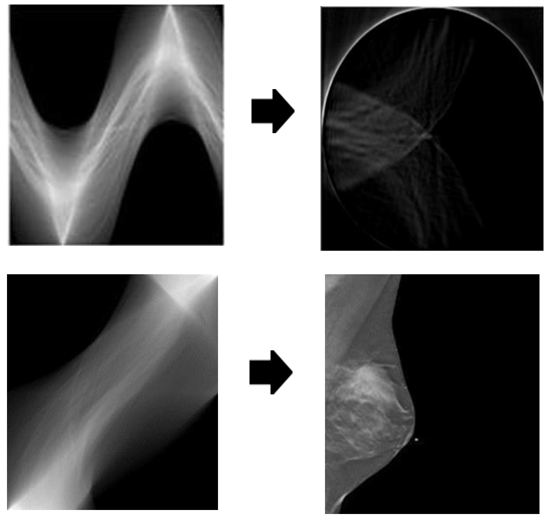

Fig. 1. Comparison of image reconstruction from 360and 180-degree sinograms

techniques and evaluating different CNN architectures. The results obtained in the detection and classification of breast lesions in DBT sinograms underscore the effectiveness of this approach, contributing to filling an important gap in digital mammography and offering a viable alternative to traditional methods.

3 Methodology

3.1 Methods

In this study, we utilized a dataset previously described in an earlier article [5], comprising a total of 2,460 breast sinograms, evenly distributed between the "Benign" and "Malignant" classes,with 1,230 samples for each class. This balanced distribution is essential for accurately interpreting the model evaluation metrics**.**

3.2 Image Processing

Several image processing techniques were implemented in Matlab to optimize the quality of the sinograms before training, including smoothing, histogram equalization, and contrast adjustment. Smoothing was performed using a median filter with a size of 25×25 pixels to reduce noise and disturbances in the data. This filter was selected for its effectiveness in eliminating noise while preserving the edges of the lesions.

Following this, histogram equalization was applied to the darker regions of the image, utilizing a threshold of 150 to differentiate the lighter areas.

This technique enhanced the visibility of the structures, making the relevant regions more discernible.

Finally, a contrast adjustment was conducted with an adjustment factor of 1.5 and a brightness level of 0.1. This adjustment highlighted the intensity differences between the areas of interest and the background while preventing saturation in the brighter regions.

These strategies were chosen to maximize the preservation of critical information regarding breast lesions while minimizing noise and optimizing visibility.

3.3 Reduction of Projection Angles

It was observed that 360-degree sinograms often failed to effectively reconstruct images, suggesting that the reconstruction process did not always preserve relevant information, as demonstrated in Fig. 1 (top image). To address this issue, we reduced the sinograms to 180-degrees, retaining only the essential projections containing critical information for breast lesion identification and localization. This reduction aimed to assess

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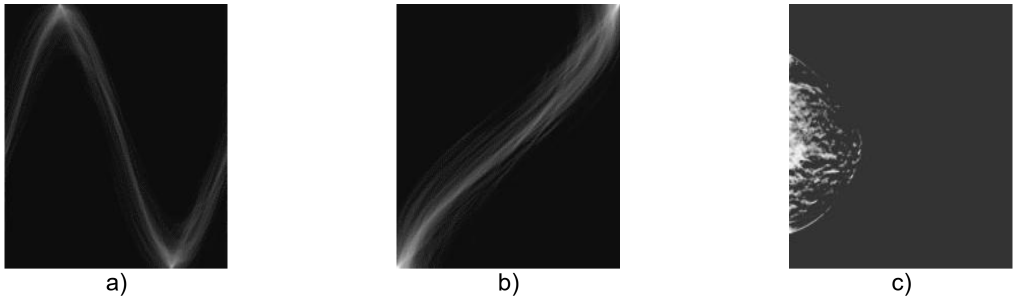

Fig. 2. Comparative Analysis of Different Stages of Image Processing in Sinogram Reconstruction

whether this portion of the sinogram contained sufficient information for accurate imagen reconstruction.

The 360 and 180-degree sinograms were generated using the Radon transform via SciPy radon() function in Python, with key operations such as array handling and image processing performed using NumPy and PIL, respectively. Projections were generated with PIL rotate(), applying bilinear interpolation, while the number of detectors and projections was parameterized. For visualization, Matplotlib plt.imshow() was used to display the sinograms. The reduction to 180-degrees was achieved by selecting a subset of projections (columns), and the resulting images were reconstructed using Image.fromarray() and saved with plt.savefig().

Preliminary analysis revealed that the 180-degree sinograms provided a reliable foundation for lesion classification, validating theeffectiveness of this approach, as shown in Fig. 1 (bottom image). This confirmed that we were working with the most relevant and accurate information for breast lesion identification and localization, ensuring the data used forclassification was both correct and representative.

3.4 Reconstruction Process

The process of image reconstruction from sinograms follows a typical approach used in computed tomography and other imaging techniques, involving three key steps: simple back projection, frequency domain filtering, and smoothing and refinement. This process was implemented using Python to ensure accurate and efficient execution of each step.

In the first step, a simple back projection was employed to generate a preliminary image. This involved rotating the sinogram projections according to the acquisition angle and summing them to obtain a laminogram, which provides a basic representation of the reconstructed image. The second step involved frequency domain filtering. The Fast Fourier Transform (FFT) of each projection of the sinogram was calculated, and a ramp filter was applied to these FFTs. This filter amplifies high frequencies to enhance image resolution. After filtering, the Inverse Fourier Transform (IFFT) was performed to convert the filtered projections back to the spatial domain, followed by back projection to construct the filtered laminogram.

In the third step, a Hamming window was appliedto the filtered projections before performing the Inverse Fourier Transform. This technique helps to reduce artifact effects and improve the quality of the final image. Finally, the laminograms were reconstructed using the windowed projections, and the resulting image was normalized.

This approach enabled visualization of three versions of the reconstructed image, each corresponding to a specific processing step. This facilitated the evaluation of the impact of filtering and windowing on the final image quality, highlighting how smoothing and refinement techniques improve the clarity and accuracy of the reconstruction. Fig. 2 shows (a) the 360-degree sinogram, (b) the sinogram reduced to 180-degrees, and (c) the image reconstructed from the 180-degree sinogram. These images illustrate and allow comparison of the contribution of each processing step to the final image quality.

In section (a), the 360-degree sinogram is presented, which contains the complete projection information from multiple angles. Section (b) shows the 180-degree cropped sinogram, which retains only the relevant data necessary for image reconstruction and eliminates redundant information. Finally, section (c) illustrates the image reconstructed from the 180-degree sinogram.

This figure highlights how each processing step, from projection angle reduction to final image reconstruction, affects the quality and accuracy of the reconstructed image. The comparison between the 360-degree and 180-degree sinograms, along with the reconstructed image, allows for the evaluation of the impact of filtering techniques and windowing on the clarity and accuracy of the final image. It underscores the importance of smoothing and refinement methods in enhancing reconstruction quality.

3.5 Training and Evaluation

Convolutional neural networks such as ResNet50, ResNet18, AlexNet, MobileNet, and InceptionV3 were used to train and evaluate the effectiveness of preprocessed sinograms and reconstructed images. The models were trained on three different datasets: 360-degree sinograms, sinograms reduced to 180-degrees, and images reconstructed via simple back projection from the generated sinograms. Performance evaluation was conducted using metrics including accuracy, recall, and F1 score. This process was implemented and analyzed using MVTec Deep Learning Tools software, facilitating detailed implementation and assessment of each configuration.

4 Results and Comparison

4.1 Model Performance

The results presented in Table 1, Table 2, and Table 3 demonstrate that 180-degree sinograms, after undergoing an image enhancement process, achieved superior performance compared to 360- degree sinograms and reconstructed images. The ResNet50 and ResNet18 models exhibited higher accuracy, recall, and F1 scores when working with180-degree sinograms:

a. **180-Degree Sinograms:** The models achieved an average F1 score of 96.64%, showing significant improvements in accuracy and recall compared to the other configurations. This result underscores the effectiveness of the preprocessing in enhancing detection and classification quality.

b. **360-Degree Sinograms:** Although still useful, these sinograms had an average F1 score of 93.45%. This indicates lower efficiency compared to 180-degree sinograms, suggesting that reducing the projection angle may enhance detection capability.

c. **Images Reconstructed by Simple Back Projection:** Despite employing a robust reconstruction process, these images had an average F1 score of 91.78%. This result highlights the loss of critical information during the back projection process, which negatively impacts the accuracy of lesion detection and classification.

4.2 Comparative Analysis

Comparative analysis reveals a clear superiority in the performance of 180-degree sinograms compared to 360-degree sinograms and images reconstructed by simple back projection. This superiority can be attributed to several key factors:

a. **Information Reduction:** 180-degree sinogramsreduce the amount of information by eliminating less relevant projections. This reduction helps convolutional neural network models focus on the most significant features for lesion identification and classification. The improved quality of 180- degree sinograms allows the models to learn cleaner and more accurate representations of lesion features.

b. **Preservation of Key Features:** By concentrating on a narrower range of projections, 180-degree sinograms retain essential information that enhances the resolution of lesion features. This preservation of key features ensures that important structures are more clearly represented, which improves

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Table 1. Training results with sinograms generated from 360-degree projections

Model	Accuracy	Recall	F1-score	Inference time	Preprocess time	Top-1error
ResNet50	95.17%	95.17%	4.83%	15.28ms	0.68ms	4.83%
ResNet18	95.59%	95.59%	4.41%	19.82ms	0.83ms	4.41%
AlexNet	91.6%	91.58%	8.4%	2.52ms	0.62ms	8.4%
MobileNet	94.75%	94.75%	5.25%	8.55ms	0.5ms	5.25%
Inceptionv3	75%	53%	25%	15ms	0.30ms	25%

Table 2. Training results with sinograms generated from 180-degree projections

Model	Accuracy	Recall	F1-score	Inference time	Preprocess time	Top-1error
ResNet50	96.64%	96.64%	96.64%	4.62ms	1.33ms	3.36%
ResNet18	98.53%	98.53%	98.53%	1.66ms	1.19ms	1.47%
AlexNet	97.27%	97.27%	97.27%	15.2ms	2.22ms	2.73%
MobileNet	96.43%	96.43%	96.43%	1.18ms	1.23ms	3.57%
Inceptionv3	89%	89.5%	89%	12ms	0.10ms	20%

Table 3. Training results in images reconstructed by simple backprojection

Model	Accuracy	Recall	F1-score	Inference time	Preprocess time	Top-1error
ResNet50	93.07%	93.07%	93.07%	3.7ms	0.83ms	6.93%
ResNet18	93.49%	93.49%	93.48%	6.76ms	1.02ms	6.51%
AlexNet	90.55%	90.55%	90.54%	9.66ms	0.8ms	9.45%
MobileNet	92.65%	92.65%	92.65%	1.26ms	0.77ms	7.35%
Inceptionv3	85%	85%	85%	10ms	5ms	15%

the model's ability to detect and classify lesions with high accuracy.

c. **Comparison with 360-Degree Sinograms:** Although 360-degree sinograms encompass a wider range of projections, this does not necessarily result in better detection quality. The larger volume of data may include redundant or less relevant projections that do not contribute additional useful information for classification. The lower F1 score of 360-degree sinograms suggests that excessive information can dilute the quality of detection and classification.

d. **Comparison with Reconstructed Images:** Images reconstructed by simple back projection were found to be less effective, exhibiting a significantly lower mean F1 score. This indicates that the simple back projection process, while robust, may not adequately preserve all critical information during reconstruction. The loss of important details at this stage adversely affects the accuracy of lesion detection and classification.

180-degree sinograms, by more effectively retaining relevant information and preserving crucial features, prove to be a more effective option for enhancing the accuracy and performance of CNN models in lesion identification and classification.

This finding underscores the importance of selecting the appropriate projection angle and processing method to optimize results in medical image analysis. The superiority of 180- degree sinograms over images reconstructed by simple back projection justifies their preferential use in lesion detection. By preserving critical information more effectively, 180-degree sinograms enable more accurate and reliable lesion detection, making them an essential tool in advanced medical image analysis and diagnosis.

5 Discussion

This study validates and extends the findings of the previous article [5], demonstrating that sinograms are not only a viable option but also offer significant improvements in the performance of breast lesion classification models. The comparison between 180-degree sinograms, 360-degree sinograms, and images reconstructed by simple back projection reveals that reducing the projection angle and applying image preprocessing are effective strategies for optimizing data quality and improving lesion detection results.

Comparative analysis showed that 180-degree sinograms, by eliminating less relevant projections, preserve crucial information better than 360-degree sinograms. This preservation of critical information facilitates more accurate lesion identification and classification, as 180-degree sinograms reduce redundant data.

Convolutional neural network models trained with these sinograms achieved superior performance in terms of accuracy, recall, and F1 score compared to models trained with 360-degree sinograms andreconstructed images.

This finding is particularly relevant from a clinical perspective. The use of 180-degree sinograms can enhance the accuracy of breast lesion diagnosis and improve treatment follow-up. By boosting the ability of models to detect lesions more precisely, 180-degree sinograms have the potential to optimize the diagnostic process and ultimately contribute to better patient outcomes.

6 Study Limitations

A limitation of this study is its focus on the binary classification of breast lesions, without exploring the detailed characterization of different types of abnormalities. This could affect diagnostic accuracy in more complex cases.

7 Conclusion

The research conducted demonstrates that enhancing sinograms with advanced image processing techniques and reducing the projection angle to 180-degrees represents a significant advance in the detection and classification of breast lesions from digital tomosynthesis. The results indicate that 180-degree sinograms when subjected to preprocessing, provide more relevant and accurate information for deep learning models compared to 360-degree sinograms and reconstructed images. This improvement is reflected in higher accuracy, recall, and F1-score in lesion identification.

The findings suggest that using 180-degree sinograms enables more effective detection and classification of breast lesions, eliminating the need for image reconstruction from sinograms. This approach not only optimizes data quality but also simplifies the process, reducing the time and resources required to achieve accurate results.

Additionally, the data augmentation techniques employed, including rotations, translations, and contrast variations, may have contributed to the enhancement of evaluation metrics, particularly in the model's ability to generalize to variations in lesion morphology.

For future research, it is recommended to explore additional image processing techniques and diverse neural network architectures. Investigating these approaches could further enhance the accuracy and efficiency of breast lesion detection, paving the way for the development of more robust and effective diagnostic methods. The comparison conducted in this study highlights that, when properly processed, sinograms can provide significant advantages over reconstructed images, reinforcing their value in clinical practice for detection and treatment monitoring.

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