Revista Brasileira de Física Médica (2024) 18:761

Computational methods applied to quality control of mammography images generated from ACR phantoms: An integrative review of current methodologies

Métodos computacionais aplicados ao controle de qualidade de imagens mamográficas geradas a partir de simuladores ACR: uma revisão integrativa das metodologias atuais

Bernardo Cecchetto[1], Carla Diniz Lopes Becker[1], Thatiane Alves Pianoschi[1], Alexandre Bacelar[2], Rochelle Lykawka[2], Janine Hastenteufel Dias[2], Viviane Rodrigues Botelho[1]

[1]Universidade Federal de Ciências da Saúde de Porto Alegre, Porto Alegre, Brazil
[2]Hospital de Clínicas de Porto Alegre, Porto Alegre, Brazil

Abstract

This study aims to conduct an integrative review of research on computational methods used for mammography quality control while addressing the issue of subjectivity in existing quality control processes. We conducted an integrative search in three electronic databases to achieve our objective. Our search included studies published within the last eleven years, with a specific focus on original research that highlights the application of computational methods for assessing mammography image quality. The selected studies have been meticulously categorized based on the methodologies employed, the input variables used for image quality assessment and the overall quality of the findings. This categorization offers a holistic overview of the current state of research in this field. Our comprehensive review of these studies underscores the immense potential of automated systems designed to enhance image quality assurance in mammography. These computational methods offer a promising solution to mitigate subjectivity issues in the quality control process related to the reading of the image. By doing so, they hold the promise of improving clinical routines and ensuring the reliability of mammography diagnostics.

Keywords: Artificial Intelligence; Mammography; Quality Control; Image processing; Phantoms; Imaging.

Resumo

Este estudo tem como objetivo realizar uma revisão integrativa de pesquisas sobre métodos computacionais utilizados para controle de qualidade em mamografia, ao mesmo tempo em que aborda a questão da subjetividade nos processos de controle de qualidade existentes. Realizamos uma busca integrativa em três bases de dados eletrônicas para atingir nosso objetivo. Nossa busca incluiu estudos publicados nos últimos onze anos, com foco específico em pesquisas originais que destacam a aplicação de métodos computacionais para avaliação da qualidade da imagem mamográfica. Os estudos selecionados foram meticulosamente categorizados com base nas metodologias empregadas, nas variáveis de entrada utilizadas para avaliação da qualidade da imagem e na qualidade geral dos resultados. Esta categorização oferece uma visão holística do estado atual da pesquisa neste campo. Nossa revisão abrangente desses estudos ressalta o imenso potencial dos sistemas automatizados projetados para melhorar a garantia da qualidade da imagem em mamografia. Esses métodos computacionais oferecem uma solução promissora para mitigar problemas de subjetividade no processo de controle de qualidade relacionado à leitura da imagem. Ao fazer isso, eles prometem melhorar as rotinas clínicas e garantir a confiabilidade do diagnóstico mamográfico.

Palavras-chaves: Inteligência artificial; Mamografia; Controle de qualidade; Processamento de imagem; Fantomas; Imagens.

1. Introduction

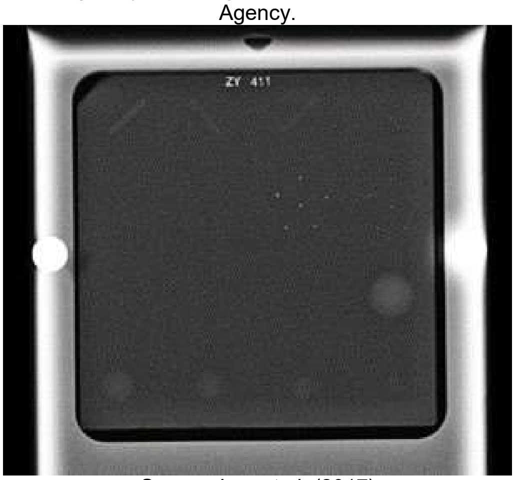
Breast cancer poses a significant global health challenge, standing as the most prevalent and deadly disease among women (1). In 2020, it recorded over 2 million new cases in women, resulting in more than 600 thousand tragic fatalities (2). Early diagnosis, primarily through mammography, is at the heart of confronting this formidable adversary. Mammography employs low-energy X-rays, necessitating breast compression to reduce tissue overlap and ensure clear visualization of anatomical structures (3,4). The World Health Organization emphasizes mammography's role in identifying cancer-related alterations before observable symptoms emerge (5).

To ensure reliable diagnoses, mammography equipment must yield images with impeccable visibility of low-contrast areas, high spatial resolution, and an extensive dynamic range (6). Routine quality control assessments, aligned with national standards and International Atomic Energy Agency (IAEA) guidelines, are indispensable(7). These assessments rely on phantoms, with the American College of Radiology (ACR) phantom being renowned in image quality assessment in mammography. These phantoms meticulously simulates both normal and abnormal breast features, including fibers, microcalcifications, and characteristic masses (6). Evaluating these structures in images can be subjective, particularly in centers with multiple operators (8).

To address these limitations and enhance image quality assurance, computational methods become imperative. This study conducts an integrative review, scrutinizing the diverse methodologies used to automate quality control procedures in mammography equipment. These methodologies employ simulator objects and equipment parameters adjustments to enhance precision and objectivity in image analysis.

The specific scientific question at the heart of this investigation revolves around improving the objectivity and precision of quality control procedures in mammography by integrating computational methods. It seeks to contribute to the field by providing a comprehensive review of the methodologies employed in automating quality control procedures and underscores their relevance in the current clinical context. Our approach involves a thorough analysis of existing literature, synthesizing findings to highlight advancements in this area and their potential to enhance the accuracy and objectivity of image assessments in breast cancer diagnosis.

Figure 1: Example of a phantom for image quality tests in mammography, following the International Atomic Energy Agency.



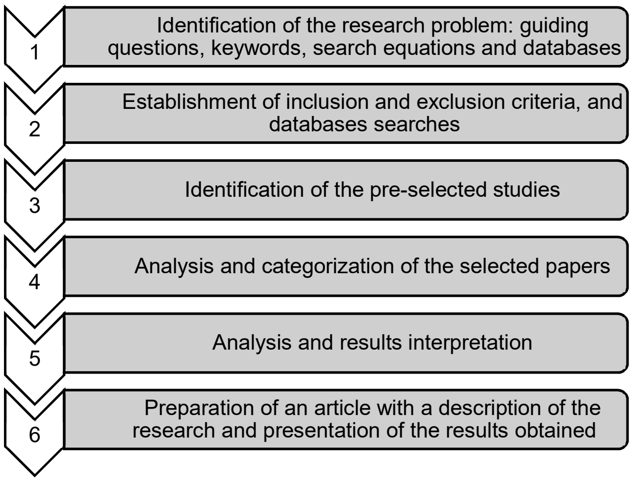
Source: Lee et al. (2017)

2. Study Development

To carry out the integrative review, we used the methodology of Strack et al. (2016) (10), which is described in Figure 2.

According to Figure 2, the first step of an integrative review is identifying the research problem. The following guiding questions were formulated: 1) What are the most recent methodologies being used in image processing of simulators? 2) What are the recent methodologies that are being applied to the quality image analyses using phantom images?; 3) What is the input information of these methodologies?; 4) What were the results achieved with the methodologies? Based on the questions, the following keywords are defined: “automat”, “learning”, “mammography”, “quality assurance”, “quality control”, “phantom”, “image”.

Figure 2: Steps of integrative systematic literature review.



Source: Adapted from Strack et al. (2016)

After the keyword definition, two search strategies were defined: the first, ((automat*) OR (learning)) AND ((mammography) AND ((quality assurance) OR (quality control)) AND (phantom) AND (image); the second, ((automate) OR (automatic) OR (learning)) AND ((mammography) AND ((quality assurance) OR (quality control)) AND (phantom) AND (image), where the wild card in ”automat*” means that will be taken all the words’ variations starting with ”automat”.

These keywords were defined to allow the selection of papers that present computational methods to image quality tests in mammography using any phantom. The search strategies were applied to the following databases: PubMed, IEEEXplore, and Science Direct. The second search question was applied in the Science Direct database because it does not accept the asterisk, which has in the first search question, wild card on the search strategy. In that way, some suffix variations of ”automat” were inserted. The second step is defining the inclusion and exclusion criteria according to Table 1 and Table 2.

Table 1: Step 2 of the integrative review: Inclusion criteria

Inclusion Criteria
Only articles published in indexed journals
Published from 2011 to 2023
English, spanish or portuguese language
Original article

Source: The author (2024).

Table 2: Step 2 of the integrative review: Exclusion criteria

Exclusion Criteria
Articles in duplication
Articles not related to the computational methods to quality controls in medical imaging equipment or computational methods that impacts directly in the image quality
Articles that use a different phantom from the ACR
Articles that don’t use images from simulation objects (phantoms)
Articles that are related to tomosynthesis exams
Articles that are related to automated control quality that do not use the ACR phantom

Source: The author (2024).

After the application of the described criteria, 240 papers were pre-selected. Moreover, the titles and abstracts were evaluated to select the publications that had the potential to answer the guiding questions and attended the inclusion and exclusion criteria. From that, fourteen articles were selected for a full reading. After a criteria analysis, seven articles were able to answer the guiding questions. This concluded step 3 of the integrative review.

Figure 3: Fluxogram of step 3 of the integrative review: identification of the pre-selected and selected studies

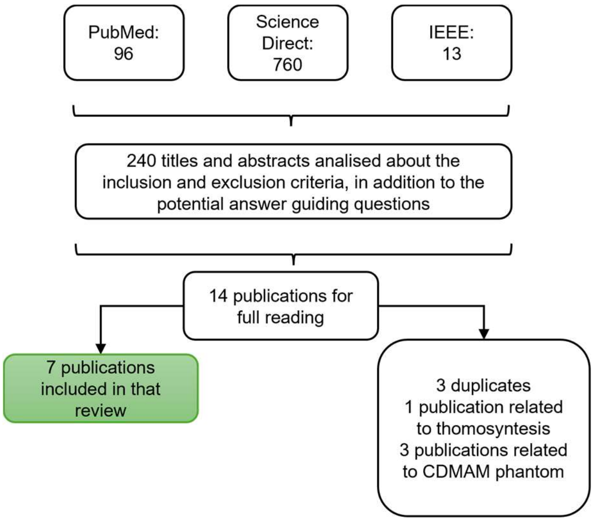


Figure 3 shows that, despite the number of publications resulting from the search, there are few papers that present computational methods applied to image quality control with ACR Digital Mammography Phantom. Most of the 240 pre-selected are related to developing new phantoms, new approaches to achieving mammography quality control, implications of using automatic exposure in mammography exams, and new approaches to automatic exposure techniques. Seven publications were included in the integrative review, and this low number makes it evident that the scientific literature still lacks studies in the area.

The questions below were used to analyze and categorize the selected articles specified in Table 3.

1. Uses image pre-processing techniques?
2. A method to assess image quality is presented?
3. Uses additional operational parameters as input (beyond phantom images)?

Table 3: Step 4 of the integrative review: Analyzes and categorization of the selected publications.

Publications Analyzed	(1)	(2)	(3)
Alvarez et al., (2012)[11]	Yes	Yes	No
Asahara and Kodera (2012)[12]	Yes	Yes	No
Chen et al. (2016)[8]	No	No	No
Guzmán et al. (2019)[13]	Yes	Yes	No
Sundell et al. (2019)[6]	Yes	Yes	No
Sundell et al. (2022)[14]	Yes	Yes	No
Ho, Hwang e Tsai (2022)[15]	Yes	Yes	No

Source: The author (2024).

2.1. Methodologies Proposed by Authors

Alvarez et al., (2012)[11] used discrete wavelet transform (DWT) and multiresolution analysis. Each target was extracted separately, and Daubechies 10 base as the mother wavelet is applied in all of the procedures to highlight the characteristics of structures present in each ROI. After DWT enhancement of the artifacts in the image, morphological procedures were used to segment the structures of interest. Then, the images are binarized to estimate the position of the artifacts. After binarization, erosion and dilation filters are applied to the binarized image to smooth the objects in the image and remove small-sized objects produced by binarization. After this image treatment, various tests were performed to ensure that the segmented objects are the corresponding structures in the phantom.

To accept the mass detection, the area, and the eccentricity (ratio between the focus of the structure and its significant axis length) of the segmented structure were tested. Only masses with an eccentricity < 30% of the item area in the phantom, were scored with grades 1.0, 0.5, or 0, respectively. For fibers acceptance, eccentricity and angle were tested. Then, only structures with eccentricity > 0.9 and an angle of 35 to 55 degrees (for fiber 1, fiber 3, and fiber 5 ROIs) or 125 to 145 degrees (for fiber 2 and fiber 4 ROIs) were considered for scoring. Then, similarly to mass groups, segmented areas ≥ 80%, within 30% and 80%, or < 30% of the item area in the phantom, were scored with grades 1.0, 0.5, or 0, respectively.

For microcalcifications, only structures with area between 0.5 to 1.5 times the corresponding microcalcifications in the phantom were maintained in the ROI. Then, each microcalcification is cross correlated with the first group, the one with the greater size. It was used as the reference image matrix. The ROIs were compared to the reference matrix using the correlation similarity parameter. Then, the microcalcifications group is scored according to the quantity that was located: if 4 to 6 microcalcifications, three microcalcifications, or < 3 microcalcifications were detected, then a score of 1.0, 0.5, or 0, respectively, is given to the group. The results obtained by the algorithm are compared by three professionals using 30 phantom images, with the tube voltage of 23 to 32 kVp and three levels of average glandular doses (AGDs) for each kVp resulting in AGDs of 0.11 to 3.4 mGy with Mo/Mo (Molybdenum/Molybdenum) as anode/filter combination. The results showed that the scores obtained by the algorithm are greater in the cases of masses and fibers. However, in microcalcifications, radiologists obtained higher scores with a low difference.

Asahara and Kodera (2012) (12) developed a computer algorithm to evaluate images of the ACR phantom automatically. It used the following methodologies: edge detection of phantom's wax, nonuniformity correction of the background, correction for magnification, and also the calculation of the cross-correlation coefficient by image matching technique. In the template image to be used in the image matching technique, the phantom's wax was removed and radiographed, where all the phantom structures could be viewed. A total of 2 template images, with phantoms with boards thickness of 2 and 4 cm, and 10 ACR phantom images were used. The algorithm results are compared with the averaged results of the observer studies by six skilled professionals.

The results showed that the proposed methodology was consistent with the evaluation scores of the skilled observers. In an evaluation of the microcalcifications groups, the algorithm made two errors, in which specklike structures were mistaken as microcalcifications. These errors could be reduced if there was improved pre-processing in the images. In another way, the study has some disadvantages, such as the removal of the wax from the phantom, which can be prejudicial to the phantom's integrity and has a high price.

Chen et al. (2016)(8) modulated a combination of operational parameters and estimated the effect of each parameter on the image quality using Taguchi's analysis. The Taguchi method uses orthogonal arrays of the experimental group to obtain extensive data about factors from only a few experiments. Thus, the authors combined analysis of variance and loss functions in the study to find the optimal combination of mammography image screening factors. Four mammography related factors were used: target, kVp, mAs, and Field-Of-View (FOV), and 2 or 3 levels of each were considered. All these factors are combined and organized into 18 groups. Based on the results, the authors concluded that kVp, mAs, and FOV are dominant factors since their variation directly impacts image quality. In this way, it is possible to detect the causes of poor image quality.

According to the author, the contrast to noise ratio (CNR) is a good metric for describing the signal amplitude relative to the background noise in an image, which is particularly useful for simple objects. The author concludes that the microcalcifications yielded the highest CNR values because the absorption coefficient is higher for these structures, which makes an essential indicator in the breast cancer screening process. However, there is a high variability for the CNR obtained in the microcalcifications, which makes it possible to infer that it is necessary to perform additional analysis to relate the results with the human visual perception. Furthermore, complement the CNR metric with perceptual quality models to obtain a better image quality metric.

In the last step, natural scene statistics (NSS) models were obtained. Two levels of CNR were extracted to identify this ability of NSS, which captured statistical consistencies of the images concerning CNR and provided relevant tools for estimating the effect of distortions in the images.

Guzmán et al. (2019) (13) provided an analysis of the ACR phantom's structures using the signal-to noise ratio (SNR), CNR, and NSS techniques. A dataset of 126 images was acquired with exposure parameters and operating conditions ranging from 40 to 80 mAs and 26 to 32 kVp. The images are generated for anode target materials configurations Mo/Mo, Mo/Rh (Molybdenum/Rhodium), and Rh/Rh. The general methodology adopted is the following: i) Capture the phantom images of mammography; ii) Select regions for quality assessment; iii) Calculate SNR, CNR, and NSS features from each phantom image structure.

The SNR describes the visibility of an object. Even though SNR does not predict human judgments of human quality, according to ACR standards, an object with an SNR higher than 50 is often detectable. After the calculation of SNR for each ROI and image, the results obtained by the author allow us to conclude that SNR is a poor predictor of human visual judgments. The lowest SNR value was recorded for exposure parameters 80 mAs and 32 kVp in Rh/Rh, and the highest SNR value was recorded for exposure parameters 40 mAs and 26 kVp in/Mo. However, the image with the lowest SNR has poor perceptual image quality, but it is greater than 50, which is the minimum value to consider an object detectable. Due to anode/filter combinations, high and low SNR were presented for the same exposure parameter due to anode/filter combinations. Therefore, there is a need to develop quality metrics that predict human judgments well.

Sundell et al. (2019)(6) developed software in order to evaluate ACR phantom images using discrete wavelet transform (DWT) and multiresolution analysis.

First, the phantom's wax area, which contains the ACR phantom structures, is located and isolated, and the image is rotated to the correct orientation. Each target (masses, fibers, and microcalcification groups) is extracted from the image and analyzed separately. The DWT and multiresolution analysis are used to enhance target visibility. The decomposition is done using Daubechies 45 base functions. After multiresolution analysis, the image is binarized. The measured length has to be 0.5-1.5cm to accept a fiber as being detected. In addition, the measured fiber angle is used as a detection requirement. A score of 0.5 points is given to a detected fiber.

The results of the automated analysis were compared with four professionals: 2 medical physicists and two medical physicist residents. It used 80 phantom images: 60 ACR phantom images randomly selected and 20 using ten different dose levels (these images were used to validate the software with different noise contents). The mean glandular doses were 0.1 – 4.1 mGy. Tube voltage was 28 kVp and exposures were 8, 11, 14, 25, 40, 64, 80, 125, 220, and 320 mAs. The anode/filter combination used is not specified.

Therefore, the mean number of detected fibers per image was 4.4 ± 0.5 and 4.4±0.6 for the automated and visual analyses. The mean number of detected microcalcification groups per image was 4.0±0.1 and 3.7±0.4 for the automated and visual analyses. Furthermore, the mean number of detected masses per image was 4.2±0.7 and 4.1±0.5 for the automated and visual analyses.

Ho, Hwang and Tsai (2022)(15) developed a framework with the aim of automating image quality control in mammography equipment. Its methodology was based on the use of the machine learning algorithm called Support Vector Machine (SVM), and tabular data extracted from the respective subimages of the ACR phantom structures.

Four hundred and sixty-one (461) phantom images were obtained, taken by medical physicists. The dataset was subdivided into training (80%) and test (20%). First, the structures of the phantom images were cropped, therefore, 16 sub-images were obtained, each corresponding to a structure: masses, fibers and microcalcifications. The study does not specify the methodology adopted to carry out this selection. Each of the structures had a class: visible (1), barely visible (0.5) and not visible (0).

Subsequently, features were extracted from each of the subimages. These features were associated with global, local, position and texture information of the image. The position feature indicates the location of the structures in the phantom. The global features represent the mean and standard deviation of the gray level, the matrix size, and the gradient of each image. Local features represent the mean and standard deviation of gray levels within the ROI and image background. Also, for local features, they extracted the contrast between the ROI and the background, the SNR, the gradient, and the texture information of each subimage. A total of 159 features were extracted.

Some different techniques were applied in order to evaluate the impact on the results, such as, for example, the Principal Component Analysis (PCA) technique, which aims to reduce the dimension of the input data. A number of components were selected that explain 95% of the data variance. The previously mentioned position characteristic was also used, and not used, in training and testing in order to evaluate its impact on results.

When carrying out training and testing using PCA, the author comments that there was no major impact on the results, however, the training time when applying it was drastically reduced. When removing and inserting the position characteristic, the author comments that there is a highly negative impact on the metrics, decreasing around 5% for each structure: fibers, masses and microcalcifications. In general, the proposed methodology obtained 90.2%, 98.2% and 88.9% accuracy for fibers, masses and microcalcifications.

Sundell et al. (2022)(14) developed an automated method for image quality control in mammography equipment using deep learning algorithms and image processing techniques.

The database used by the author consisted of daily image acquisition routines in mammography image quality control tests. In order to obtain a wider database, that is, images with variations in quality, the author changed the noise of some images, either decreasing or increasing it. In total, 800 unaltered images were used, and 1840 images with their noise altered. After that, the images were processed. To do this, the author initially cut out the internal region of the phantom in two steps: first, the phantom area was extracted, based on the difference in the region's signal with the image background; Second, the internal area of the phantom was extracted by detecting the abrupt differences of pixels in the x and y axis. After that, the phantom images were rotated, when necessary. Each of the image structures was extracted, that is, masses, fibers and microcalcifications, generating, for each phantom image, 16 subimages. The subimages were normalized and processed later. Low-frequency background non-uniformities were extracted from the subimages using two-dimensional polynomial approximations. Fifth-order polynomial approximations were applied to the fibers, and first-order approximations to the microcalcifications and masses. Ninety percent (90%) of the images were designated for training, and 10% for testing. After that, the training steps were applied.

Eight CNN architectures were trained in order to classify images as visible, or barely visible (class 1), or not visible (class 0). The best configuration was the one that used 6 convolutional layers, achieving an overall accuracy of 95.2%. For fibers, a mean and standard deviation of the number of visible structures of 4.3 ± 1.4 and 4.4 ± 1.3 were obtained for professionals and the automated method. For microcalcifications, 3.8 ± 0.8 for both professional and automated methods. And for the masses, 4.4 ± 0.9 and 4.5 ± 0.8 for professionals and the automated method, respectively.

2.2. General Discussion

In this study, we conducted an integrative review of computational methods applied to image quality control in mammography. After a thorough selection process, we analyzed fourteen articles and identified seven that were able to address our guiding questions. Notably, our findings highlight a scarcity of research in this specific area of study, as the majority of the pre-selected papers focused on topics such as phantom development and novel approaches to mammography quality control.

When we compare our results to existing literature, it becomes evident that the field of computational methods for mammography image quality control is still in its infancy. While some promising approaches have been proposed, such as the use of DWT and machine learning algorithms, there remains a need for further validation and refinement. For instance, Alvarez et al. (2012)(11) presented a method involving DWT and morphological procedures, showing potential for mass and fiber detection. However, their study requires further clinical validation to assess its practical relevance.

Some crucial aspect for consideration is the impact of glandular dose, which significantly influences both image quality and patient welfare (16). As elucidated in prior studies, certain images analyzed for evaluation were carefully curated within specific glandular dose ranges, enhancing the robustness and reliability of the investigation. Nevertheless, this paper directs its focus primarily towards the discourse surrounding its computational methodologies. The aim is to comprehensively grasp how these approaches can influence mammography services, particularly in terms of image quality control across mammography equipment, as presented below in the discussions.

Asahara and Kodera (2012)(12) introduced a computer algorithm for ACR phantom image evaluation, aligning well with skilled observers. Nevertheless, their method's limitation of removing phantom wax and its potential impact on phantom integrity should be addressed in future research. Chen et al. (2016) (8) provided insights into the critical role of operational parameters in image quality but noted the need for further analysis to relate these findings to human perception.

Guzman et al. (2019)(13) explored SNR and CNR techniques but highlighted the need for improved quality metrics. Sundell et al. (2019)(6) leveraged DWT and multiresolution analysis, achieving promising results in automated image quality control. Ho, Hwang, and Tsai (2022)(15) introduced a machine learning-based framework, offering high accuracy in detecting various structures in ACR phantom images. Sundell et al. (2022)(14) notably introduced an automated method using deep learning algorithms and image processing techniques, achieving impressive accuracy in classifying images as visible, barely visible, or not visible. This approach represents a significant advancement in the field.

However, as we discuss these findings, it's essential to acknowledge certain biases and limitations in our study. Firstly, our search may have missed relevant papers due to variations in keywords and indexing practices. Additionally, the limited number of selected articles emphasizes the paucity of research in this field, limiting the generalizability of our findings. Also, the absence of clinical validation in some proposed methods necessitates future studies to bridge the gap between computational techniques and practical clinical applications.

3. Conclusion

In conclusion, our integrative review of the existing literature on computational methods for mammography image quality control highlights the nascent nature of this field. While several promising approaches have been proposed, including techniques like DWT, machine learning algorithms and advanced image processing, there is still much ground to cover. These methodologies could potentially decrease the subjectivity of image quality control in mammography equipment. Therefore, the studies we examined showcase the potential of these methodologies.

However, a critical examination of the literature also reveals certain limitations and areas that require attention. Moreover, the relatively small number of selected articles underscores the scarcity of research in this domain, emphasizing the need for expanded investigations. Additionally, the absence of clinical validation in some of the proposed methods underscores the gap between computational techniques and their practical clinical application.

Considering these findings, it is evident that the field of computational methods for mammography image quality control is in its early stages and requires sustained dedication and innovation. Future research endeavors must focus on refining existing methods. Bridging the gap between computational techniques and clinical practice through rigorous validation will be pivotal in harnessing the full potential of these approaches.

Ultimately, the pursuit of improved mammography image quality control holds profound clinical significance. High-quality mammography images are fundamental to accurate breast cancer diagnosis and early detection, which can significantly impact patient outcomes. As we move forward, continued collaboration between medical physicists, researchers, clinicians, and technologists will be essential to advance the state of the art in this critical field, ensuring that women receive the highest standard of care in breast cancer screening and diagnosis.

References

1 World Health Organization. Estimated age-standardized incidence rates (World) in 2020, worldwide, both sexes, all ages. 2021.https://gco.iarc.fr/today/data/factsheets/cancers/20-Breast-fact-sheet.pdf (accessed 2 Feb2021).

2 World Health Organization. Cancer Today. 2020.https://gco.iarc.fr/today/online-analysis-pie?v=2020&mode=cancer&mode_population=continents&population=900&populations=900&key=total&sex=2&cancer=39&type=1&statistic=5&prevalence=0&population_group=0&ages_group%5B%5D=0&ages_group%5B%5D=17&nb_items=7&group (accessed 13 Jul2021).

3 Kretz T, Mueller K-R, Schaeffter T, Elster C. Mammography Image Quality Assurance Using Deep Learning. *IEEE Trans Biomed Eng* 2020; **67**: 3317–3326.

4 Serwan E, Matthews D, Davies J, Chau M. Mammographic compression practices of force- and pressure-standardisation protocol: A scoping review. *J Med Radiat Sci* 2020; **67**: 233–242.

5 World Health Organization. Breast cancer. 2021.https://www.who.int/news-room/fact-sheets/detail/breast-cancer (accessed 13 Jul2021).

6 Sundell V-M, Mäkelä T, Meaney A, Kaasalainen T, Savolainen S. Automated daily quality control analysis for mammography in a multi-unit imaging center. *Acta Radiol* 2019; **60**: 140–148.

7 *Quality Assurance Programme for Digital Mammography*. INTERNATIONAL ATOMIC ENERGY AGENCY: Vienna, 2011https://www.iaea.org/publications/8560/quality-assurance-programme-for-digital-mammography.

8 Chen C-Y, Pan L-F, Chiang F-T, Yeh D-M, Pan L-K. Optimizing quality of digital mammographic imaging using Taguchi analysis with an ACR accreditation phantom. *Bioengineered* 2016; **7**: 226–234.

9 Lee Y, Tsai D-Y, Shinohara N. Computerized quantitative evaluation of mammographic accreditation phantom images. *Med Phys* 2010; **37**: 6323–6331.

10 Strack MH, da Silva Bauer M, Mattos LB, Cazella SC, Magalhães CR. Jogos digitais aplicados à promoção do autocuidado em saúde no escolar: uma revisão integrativa. *RENOTE* 2016; **14**.

11 Alvarez M, Pina DR, Miranda JRA, Duarte SB. Application of wavelets to the evaluation of phantom images for mammography quality control. *Phys Med Biol* 2012; **57**: 7177–7190.

12 Asahara M, Kodera Y. Computerized scheme for evaluating mammographic phantom images. *Med Phys* 2012; **39**: 1609–1617.
13 Guzmán VC, Darío Benítez Restrepo H, Hurtado ES. Natural Scene Statistics of Mammography Accreditation Phantom Images. In: *2019 XXII Symposium on Image, Signal Processing and Artificial Vision (STSIVA)*. 2019, pp 1–5.
14 Sundell V-M, Mäkelä T, Vitikainen A-M, Kaasalainen T. Convolutional neural network-based phantom image scoring for mammography quality control. *BMC Med Imaging* 2022; **22**: 216.
15 Ho P-S, Hwang Y-S, Tsai H-Y. Machine learning framework for automatic image quality evaluation involving a mammographic American College of Radiology phantom. *Physica Medica* 2022; **102**: 1–8.
16 Fausto AMF, Lopes MC, de Sousa MC, Furquim TAC, Mol AW, Velasco FG. Optimization of image quality and dose in digital mammography. *J Digit Imaging* 2017; **30**: 185–196.

Contact

Bernardo Cecchetto
Universidade Federal de Ciências da Saúde de Porto Alegre
R. Sarmento Leite, 245, Porto Alegre, Brazil
bernardoc@ufcspa.edu.br