UNIVERSITI TEKNOLOGI MARA
MATHEMATICS LETTERS
https://sites.google.com/tmsk.uitm.edu.my/mathematicsletters

Review on Feature Extraction Methods In Computer-Aided Detection Systems on Mammogram Images

[1]Nur Auni Nadia Mohd Zin, [2]Siti Salmah Yasiran & [3,*]Suhaila Abd Halim
[1,2,3]Centre of Mathematical Sciences, Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia.
nadia.auni9964@gmail.com
salmahyasiran@uitm.edu.my
suhaila889@uitm.edu.my
*Corresponding author

Received: 3/4/2026 Revised: 10/4/2026 Accepted: 15/4/2026 Published: 30/4/2026

ABSTRACT

Breast cancer is among the main causes of cancer-related deaths worldwide. Early detection and accurate diagnosis are essential in getting proper treatment. Mammographic imaging that is widely used in screening, often suffers from low contrast and subtle lesion visibility that becomes a challenge for manual interpretation. Feature extraction method plays a significant role in enhancing computer-aided diagnosis by isolating meaningful patterns from mammogram images. This review investigates various feature extraction approaches categorized into statistical, transform-based, keypoint-based, and learning-based methods. There is no single method consistently outperforming others, but combining method often enhances performance. This review highlights the diversity of approaches and concludes that the choice of method should consider dataset characteristics, computational cost, and clinical requirements, while future work should focus on hybridization, interpretability, and dataset standardization.

Keywords: breast cancer, computer-aided diagnosis, feature extraction, image analysis, mammogram

INTRODUCTION

Breast cancer is the most common cancer among women worldwide and one of the leading causes of cancer related death. Early detection is an important part to play in ensuring that the mortality rate due to cancer can be reduced and can improve the prognosis of breast cancer patients (World Health Organization, 2025). For early detection, mammography plays an important role in getting the diagnosis done. However, the produced mammogram images is not a high contrast, only highlight the cancer part and clear which makes it complicated for the radiologists to interpret the accurate results and highly likely to cause false error. By using computer-aided detection (CAD) systems, it helps in addressing the possibility of human error in interpreting the result by interpreting it automatically.

In CAD systems there are 4 main stages which are image pre-processing, segmentation, feature extraction and feature selection and classification in order to make breast cancer diagnosis. Feature extraction is the important part throughout the whole process as it derives the important part of the image before it being run for the diagnosis in classification (El-Naqa et al., 2002). Figure 1 illustrates the typical workflow of a CAD system used for mammogram analysis, highlighting where feature extraction fits in the pipeline. Starting from the retrieval of mammogram images, the process goes through image preprocessing, feature extraction, feature selection and classification, which end with the diagnostic output.

Figure 1

Generic Workflow of CAD System

Throughout the years, researchers have explored a wide range of feature extraction method which are statistical, transform-based, keypoint-based and learning-based methods. The approach done by researchers differ in terms of the robustness, computational cost and the effectiveness of the method dependence on the conditions of the imaging data. Feature extraction is a process that identify important patterns or structures of an image.

The objectives of this review can be divided into three which are to review and analyse feature extraction methods used on mammogram images, to evaluate the methods performance, accuracy and efficiency and to highlight the advantages and limitations of each method. However, feature extraction methods face several general limitations which are sensitivity to noise, lack of robustness under different conditions such as rotation, scale and contrast and the dependency on domain-specific knowledge (El-Naqa et al., 2002; Jasmine et al., 2011; Shen et al., 2019).

FEATURE EXTRACTION METHOD

This section categorizes feature extraction methods which are statistical-based, transform based, keypoint-based and learning-based method. For each method, the principles, the application on mammogram images, trends and limitations will be highlighted.

Statistical Based Method

Statistical method is an early approach on feature extraction for mammogram analysis based on its simplicity and effectiveness in capturing texture from the image (Haralick et al., 1973; Shen et al., 2019). The method focusses on quantifying the intensify distribution images through statistical descriptors. Statistical features include mean, variance, skewness, and second-order texture descriptors such as such as those derived from the Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM). Introduced by Haralick et al. (1973), GLCM-based features have been adopted in analysing mammogram images by using the ability on capturing spatial relationships of pixel intensities. GLCM is used to quantify the frequency of pairs of pixel values at a specific distance and orientation. This forms a matrix form which become the basis for several statistical descriptor that detect the spatial texture such as contrast, energy, homogeneity and correlation to differentiate between benign and malignant lesions in digitized mammograms which help in achieving an accuracy of over 80% (Mudigonda et al., 2000). Mathematically it is defined by:

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \tag{1}$$

where P is the normalized probability of the co-occurrence of pixel in the image. The expressions allow the quantification of texture sharpness. A first-order statistics which can be classify as histogram-based descriptors was employed by Mudigonda et al. (2001) in demonstrating the effectiveness of distinguishing microcalcifications from normal tissues. GLRLM was explored for lesion detection by extracting run-length features which are short-run emphasis and long-run emphasis in identifying clustered microcalcifications. Improvements have been made based on this method by combining statistical features with machine learning classifier such as Support Vector Machines (SVM), Artificial Neural Networks (ANN) and Random Forests which resulted in better performance across different datasets (Milosevic et al., 2017). However, this method is sensitive upon characteristic of the image used such as the image quality and noise which make the result of the image is not robust under different conditions. Therefore, the effectiveness of this method highly depends on preprocessing stage and normalization method.

Transform-Based Method

Transform–Based Method is a method that analyse images through the frequency or spatial-frequency domain in order to extract features that are invariant to translation, rotation and illumination. The methods used are effective at capturing information of texture and shape that may not be easy to translate in spatial domain. In mammographic image, the methods have been used in identifying structures such as masses and microcalcifications. Wavelet Transform which is one of the most uses transform-based method decomposes an image into sub-bands at different scale and orientations. The multiresolution analysis allows the extraction of texture that are both fine and coarse. Laine & Fan (1993) utilized the wavelet packets in extracting texture features from mammogram images which is recorded by the author that there is a significant improve of mass calcification accuracy. Wavelet-based features performance is better than spatial domain features in term of capturing high frequency components that is associated with malignant regions (Berbar, 2018). The 2D Discrete Wavelet Transform (DWT) of an image can be mathematically defined as:

$$\begin{gathered} W_\phi(j_0,m,n) = \sum_x \sum_y f(x,y)\phi_{j_0,m,n}(x,y) \\ W_\psi^i(j,m,n) = \sum_x \sum_y f(x,y)\ \psi_{j,m,n}^i(x,y), \qquad i = \{H,V,D\} \end{gathered} \tag{2}$$

where ϕ is the scaling function and ψ is the wavelet functions horizontal (H), vertical (V) and diagonal (D) directions. Another method that can be highlighted is Fourier Transform that captures global frequency. For mammogram images, this method lacks spatial localization which limits the localized abnormalities identification. In overcoming the limitations, Short-Time Fourier Transform (STFT) and Gabor filters have been introduced. Gabor filters are well suited in texture analysis of an image as it provides optimal joint localization in both spatial and frequency domains. It is defined as sinusoidal waves that is modulated by a Gaussian envelope and usually applied in a filter bank configuration. Study related to mammogram images on Gabor filter bank were done by Zhang et al. (2014) of texture classification to achieve the robust performance at differentiating between dense and fatty issues. The study emphasised the filter's ability in capturing multi-scale and multi-orientation which make it valuable in describing complex pattern of mammographic images.

Another extension of wavelets which is Contourlet Transform has also been used for feature extraction as it is able to capture directional edges and smooth contours. A study by Jasmine et al. (2011) used Contourlet features with the support of SVMs as the combination in classifying mammograms. This recorded a higher classification accuracy compared to accuracy recorded by DWT. This can be highlighted as the trend toward using directional transforms as it is better at modeling the natural geometry of medical images. Even through the strengths that were listed, this method also has its limitations. Transform-based method requires a rigid parameter selection and can also be computationally intensive. Furthermore, the performance of the method degrades when it is applied on low-quality or noisy images which are the characteristic of mammographic images in general unless it is paired with effective preprocessing.

Keypoint-Based Method

Keypoint-based method can be defined as a method that is to detect and describe distinct points in an image that is most of the time invariant to transformations such as scale, rotation, and illumination. This method is specifically important in analysing mammographic images due to its ability in focusing on local structures like microcalcifications, masses and distortions which are important features on an image as indicator for breast cancer diagnosis (Loizidou et al., 2023; Lowe, 2004). One of the widely used keypoint detectors which was earliest to be introduced is the Scale-Invariant Feature Transform (SIFT) is a feature that identify keypoints based on difference of Gaussians in the scale space and later represent through orientation histograms (Lowe, 2004). Its robustness to scale and rotation has made it a reference point in medical imaging applications. In mammogram analysis, SIFT has been used to detect suspicious regions with variations in local gradients that could indicate abnormal tissue patterns (Deshmukh & Bhosle, 2016). The Speeded-Up Robust Features (SURF) algorithm offers an improvement in computational efficiency by approximating Gaussian filtering with box filters and using integral images. Its application in mammogram analysis is focused on identifying rapid intensity changes around lesion boundaries and texture discontinuities (Insalaco et al., 2015). Past study has also shown that by combining SURF keypoints with SVM for benign and malignant classification, the detection accuracy is enhanced (Salleh et al., 2017).

Another method that can be highlighted is Binary Robust Invariant Scalable Keypoints (BRISK) which uses binary descriptors and circular sampling patterns in detecting and describing keypoints (Leutenegger et al., 2011). As descriptor, BRISK has recorded a good performance in term of its speed and low computational complexity. When used in conjunction with a fast descriptor matching approach, BRISK enables efficient feature matching between different mammogram views (Ouddai et al., 2023). KAZE and Accelerated-KAZE (A-KAZE) are more recent innovations that operate in nonlinear scale space, preserving edge information while reducing noise sensitivity (Alcantarilla et al., 2012, 2013). KAZE uses nonlinear diffusion filtering to detect fine-grained structures while maintaining high localization accuracy. However, it is computationally expensive, leading to the development of A-KAZE, which utilizes Fast Explicit Diffusion (FED) schemes for greater speed without compromising performance (Alcantarilla et al., 2013). These methods have shown promise in enhancing lesion detection in low-contrast mammograms.

Keypoint-based methods have also been incorporated into hybrid feature extraction pipelines, often paired with statistical or deep learning approaches. For instance, keypoint descriptors extracted using SIFT or KAZE can be fused with GLCM texture features or CNN-based embeddings to improve classification accuracy (Shen et al., 2019). Despite their advantages, keypoint-based methods have limitations. They may generate redundant or non-discriminative points in homogeneous regions of mammograms, and their performance heavily relies on the quality of the preprocessing stage. Furthermore, rotation invariance is not always guaranteed methods like BRISK or KAZE require additional orientation assignment to ensure consistency (Alcantarilla et al., 2013; Leutenegger et al., 2011). Overall, keypoint-based feature extraction methods offer strong localization and scale/rotation invariance properties that make them suitable for detecting subtle yet clinically significant patterns in mammographic images. However, careful integration and optimization are needed to fully leverage their potential, especially in low-resolution or noisy clinical data.

Learning-Based Method

Learning-based feature extraction methods, particularly those driven by deep learning, have revolutionized mammographic image analysis by enabling automatic discovery of complex patterns from raw data without manual feature engineering. These methods rely on large datasets to train models that is primarily convolutional neural networks (CNNs) that learn hierarchical features directly from the image pixels, capturing both low-level textures and high-level semantic information (Kooi et al., 2017). In mammography, CNNs are frequently used to extract features for classifying normal and abnormal tissues, detecting masses, and assessing breast density. A widely adopted architecture is AlexNet, which demonstrated early success in image classification tasks and was later adapted for breast lesion classification with promising results (Ayer et al., 2010). Deeper models like VGGNet and ResNet have since been employed for better feature abstraction and generalization across mammographic datasets (Arevalo et al., 2016). For instance, VGG-16 combined with region proposals has been used to extract discriminative features around mass boundaries, significantly boosting detection sensitivity (Divya et al., 2025).

Transfer learning is a common strategy in mammographic analysis due to the limited size of annotated datasets. Pretrained CNNs on large datasets like ImageNet are fine-tuned on mammographic images to adapt learned features to domain-specific patterns (Castro-Tapia et al., 2021). This approach has proven effective in boosting performance while reducing the need for extensive labelled medical data. Several studies reported improved classification accuracy when transfer learning was combined with traditional features such as histogram of oriented gradients (HOG) or Local Binary Pattern (LBP) (Sajid et al., 2023). Hybrid learning-based systems often integrate deep features with statistical or keypoint-based features to leverage the advantages of both data-driven and hand-crafted methods. For example, features extracted from the intermediate layers of CNNs have been fused with histogram-based or keypoint-based features, leading to more robust lesion classification. Such fusion strategies have been reported to improve diagnostic accuracy, particularly in distinguishing benign from malignant cases (Vijayalakshmi et al., 2025). Despite their impressive performance, learning-based methods face several limitations. The requirement for large, annotated datasets poses a challenge in the medical domain where expert labelling is time-consuming and costly. Furthermore, deep learning models tend to act as black boxes, making it difficult to interpret the extracted features, which is critical in clinical decision-making (Jin et al., 2022). To address these concerns, research has explored explainable AI approaches such as Grad-CAM, saliency maps, and attention mechanisms to highlight important image regions contributing to model predictions (Salahuddin et al., 2022).

Another challenge is the generalization of trained models across datasets acquired from different machines or populations. Domain adaptation methods and image standardization methods have been proposed to mitigate this issue and improve cross-dataset robustness (Kelly et al., 2019). Some recent studies also explore self-supervised learning to extract informative representations without manual labels, which holds promise for future research in mammography (Karagoz & Nalbantoglu, 2024; Miller et al., 2022). Learning-based feature extraction continues to evolve rapidly, showing the potential to outperform traditional methods when enough high-quality data and appropriate model architectures are available. The future direction involves enhancing interpretability, reducing dependency on large datasets, and integrating clinical knowledge into network design to ensure reliability and trust in medical settings.

Critical Appraisal and Research Directions

While each category of feature extraction method which are statistical, transform-based, keypoint-based, and learning-based has demonstrated strengths in mammographic analysis, none offers a universally optimal solution across all diagnostic tasks or datasets. Statistical methods such as GLCM provide interpretable texture metrics but lack robustness to variations in image resolution, scale, and orientation. Transform-based methods offer frequency domain insights but often fail to preserve spatial information critical to localizing subtle lesions. Similarly, keypoint-based methods, although useful for detecting invariant features, may not capture contextual patterns or high-level semantics required in complex diagnostic scenarios. Moreover, even advanced detectors like KAZE and BRISK may perform inconsistently depending on certain images type such as those in low contrast or repetitive textures which in mammography influenced by breast density and lesion contrast (Leutenegger et al., 2011; Lowe, 2004; Mudigonda et al., 2000).

Learning-based methods have shown substantial gains in performance but are heavily data-dependent, computationally intensive, and often criticized for their lack of interpretability (Jin et al., 2022). Despite their powerful abstraction capabilities, deep models tend to act as black boxes, and their decisions may be difficult for clinicians to validate. In addition, biases from limited or imbalanced training datasets may lead to unreliable generalization when applied to real-world screening settings (Kelly et al., 2019). These limitations, however, do not negate the potential of each method. Rather, they underscore the importance of combining complementary approaches. For instance, handcrafted features can support interpretability and augment deep models in data-scarce environments. Similarly, frequency-based features can enrich spatial representations, and keypoints can anchor region-based learning. Research trends increasingly favour hybrid frameworks that merge the strengths of multiple methods, leading to better classification accuracy, robustness to variability, and improved diagnostic value (Berbar, 2018; Sajid et al., 2023).

Future studies should also consider standardizing datasets, benchmarking protocols, and performance metrics to allow fair and reproducible comparisons across methods. There is significant room for improving computational efficiency, enhancing explainability, and customizing methods to clinical workflows. Despite the emergence of dominant trends such as deep learning, classical methods remain relevant, particularly when tailored for specific image characteristics, resource-constrained settings, or interpretability-driven tasks.

CONCLUSION

Feature extraction is a vital stage in mammographic image analysis, serving as the foundation for accurate computer-aided diagnosis. This review has explored various methods that are statistical, transform-based, keypoint-based, and learning-based each offering distinct advantages depending on the characteristics of the mammogram images and the clinical objectives. While statistical and transform-based methods remain reliable for capturing texture and frequency-based features, they often lack robustness under complex conditions such as scale and rotation. Keypoint-based methods offer better invariance and localization but may require extensive tuning and are sensitive to image quality. Learning-based methods, particularly deep learning, provide superior performance in many cases but demand large, annotated datasets, high computational resources, and lack interpretability. No single method proves to be universally optimal across all imaging scenarios. Instead, the combination of multiple feature extraction approaches tends to enhance diagnostic performance. Future research should emphasize hybrid methods, algorithm interpretability, and the use of standardized datasets to enable fair comparison and clinical integration. By addressing current limitations and focusing on application-specific customization, feature extraction can continue to evolve and play a crucial role in the early and accurate detection of breast cancer through mammography.

ACKNOWLEDGEMENT

The author(s) would like to acknowledge Universiti Teknologi MARA (UiTM) and Faculty of Mathematical and Computer Sciences (FSKM) for their support and contributions.

Conflict of Interest
The authors have no conflicts of interest to declare.

Non-funded
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

Alcantarilla, P. F., Bartoli, A., & Davison, A. J. (2012). KAZE Features. In A. Fitzgibbon, S. Lazebnik, P. Perona, Y. Sato, & C. Schmid (Eds.), *Computer Vision – ECCV 2012* (pp. 214–227). Springer Berlin Heidelberg.

Alcantarilla, P. F., Nuevo, J., & Bartoli, A. (2013). Fast Explicit Diffusion for Accelerated Features in Nonlinear Scale Spaces. *British Machine Vision Conference*. https://api.semanticscholar.org/CorpusID:8488231

Arevalo, J., González, F. A., Ramos-Pollán, R., Oliveira, J. L., & Guevara Lopez, M. A. (2016). Representation learning for mammography mass lesion classification with convolutional neural networks. *Computer Methods and Programs in Biomedicine*, *127*, 248–257. https://doi.org/https://doi.org/10.1016/j.cmpb.2015.12.014

Ayer, T., Alagoz, O., Chhatwal, J., Shavlik, J. W., Kahn Jr, C. E., & Burnside, E. S. (2010). Breast cancer risk estimation with artificial neural networks revisited. *Cancer*, *116*(14), 3310–3321. https://doi.org/https://doi.org/10.1002/cncr.25081

Berbar, M. A. (2018). Hybrid methods for feature extraction for breast masses classification. *Egyptian Informatics Journal*, *19*(1), 63–73. https://doi.org/https://doi.org/10.1016/j.eij.2017.08.001

Castro-Tapia, S., Castaneda-Miranda, C. L., Olvera-Olvera, C. A., Guerrero-Osuna, H. A., Ortiz-Rodriguez, J. M., Martinez-Blanco, M. del R., Diaz-Florez, G., Mendiola-Santibanez, J. D., & Solis-Sanchez, L. O. (2021). Classification of breast cancer in mammograms with deep learning adding a fifth class. *Applied Sciences*, *11*(23), 11398.

Deshmukh, J., & Bhosle, U. (2016). SIFT with associative classifier for mammogram classification. *2016 International Conference on Signal and Information Processing (IConSIP)*, 1–5. https://doi.org/10.1109/ICONSIP.2016.7857497

Divya, G., Arvind, S., Premalatha, B., Aruna Suhasini Devi, Y., Kumara Swamy, M., & Bahadur Pandey, L. (2025). Evaluation on Obtaining Advanced Features of CNN's Deep Learning VGG 16 Architecture for Breast Cancer Detection. In V. Sakalauskas, A. Bajaj, A. Abraham, K. R. Madhavi, & P. Manghirmalani Mishra (Eds.), *Bio-Inspired Computing* (pp. 517–524). Springer Nature Switzerland.

El-Naqa, I., Yang, Y., Wernick, M. N., Galatsanos, N. P., & Nishikawa, R. M. (2002). A support vector machine approach for detection of microcalcifications. *IEEE Transactions on Medical Imaging*, *21*(12), 1552–1563. https://doi.org/10.1109/TMI.2002.806569

Haralick, R. M., Shanmugam, K., & Dinstein, I. (1973). Textural Features for Image Classification. *IEEE Transactions on Systems, Man, and Cybernetics*, *SMC-3*(6), 610–621. https://doi.org/10.1109/TSMC.1973.4309314

Insalaco, M., Bruno, A., Farruggia, A., Vitabile, S., & Ardizzone, E. (2015). An Unsupervised Method for Suspicious Regions Detection in Mammogram Images. *ICPRAM (2)*, 302–308.

Jasmine, J. S. L., Baskaran, S., & Govardhan, A. (2011). An automated mass classification system in digital mammograms using contourlet transform and support vector machine. *Int. J. Comput. Appl*, *31*(9), 54–61.

Jin, D., Sergeeva, E., Weng, W., Chauhan, G., & Szolovits, P. (2022). Explainable deep learning in healthcare: A methodological survey from an attribution view. *WIREs Mechanisms of Disease*, *14*(3), e1548.

Karagoz, M. A., & Nalbantoglu, O. U. (2024). A self-supervised learning model based on variational autoencoder for limited-sample mammogram classification: MA Karagoz and OU Nalbantoglu. *Applied Intelligence*, *54*(4), 3448–3463.

Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. *BMC Medicine*, *17*(1), 195.

Kooi, T., Litjens, G., van Ginneken, B., Gubern-Mérida, A., Sánchez, C. I., Mann, R., den Heeten, A., & Karssemeijer, N. (2017). Large scale deep learning for computer aided detection of mammographic lesions. *Medical Image Analysis*, *35*, 303–312. https://doi.org/https://doi.org/10.1016/j.media.2016.07.007

Laine, A., & Fan, J. (1993). Texture classification by wavelet packet signatures. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *15*(11), 1186–1191. https://doi.org/10.1109/34.244679

Leutenegger, S., Chli, M., & Siegwart, R. Y. (2011). BRISK: Binary Robust invariant scalable keypoints. *2011 International Conference on Computer Vision*, 2548–2555. https://doi.org/10.1109/ICCV.2011.6126542

Loizidou, K., Elia, R., & Pitris, C. (2023). Computer-aided breast cancer detection and classification in mammography: A comprehensive review. *Computers in Biology and Medicine*, *153*, 106554. https://doi.org/https://doi.org/10.1016/j.compbiomed.2023.106554

Lowe, D. G. (2004). Distinctive Image Features from Scale-Invariant Keypoints. *International Journal of Computer Vision*, *60*(2), 91–110. https://doi.org/10.1023/B:VISI.0000029664.99615.94

Miller, J. D., Arasu, V. A., Pu, A. X., Margolies, L. R., Sieh, W., & Shen, L. (2022). Self-supervised deep learning to enhance breast cancer detection on screening mammography. *ArXiv Preprint ArXiv:2203.08812*.

Milosevic, Marina, Jovanovic, Zeljko, & Jankovic, Dragan. (2017). A comparison of methods for three-class mammograms classification. *Technology and Health Care*, *25*(4), 657–670. https://doi.org/10.3233/THC-160805

Mudigonda, N. R., Rangayyan, R., & Desautels, J. E. L. (2000). Gradient and texture analysis for the classification of mammographic masses. *IEEE Transactions on Medical Imaging*, *19*(10), 1032–1043. https://doi.org/10.1109/42.887618

Mudigonda, N. R., Rangayyan, R. M., & Desautels, J. E. L. (2001). Detection of breast masses in mammograms by density slicing and texture flow-field analysis. *IEEE Transactions on Medical Imaging*, *20*(12), 1215–1227. https://doi.org/10.1109/42.974917

Ouddai, G., Hamdi, I., & Ghézala, H. Ben. (2023). A Comparative Study of BRISK, ORB and DAISY Features for Breast Cancer Classification. *ICPRAM*, 964–970.

Sajid, U., Khan, R. A., Shah, S. M., & Arif, S. (2023). Breast cancer classification using deep learned features boosted with handcrafted features. *Biomedical Signal Processing and Control*, *86*, 105353. https://doi.org/https://doi.org/10.1016/j.bspc.2023.105353

Salahuddin, Z., Woodruff, H. C., Chatterjee, A., & Lambin, P. (2022). Transparency of deep neural networks for medical image analysis: A review of interpretability methods. *Computers in Biology and Medicine*, *140*, 105111. https://doi.org/https://doi.org/10.1016/j.compbiomed.2021.105111

Salleh, S., Mahmud, R., Rahman, H., & Yasiran, S. S. (2017). Speed up robust features (surf) with principal component analysis-support vector machine (pca-svm) for benign and malignant classifications. *Journal of Fundamental and Applied Sciences*, *9*(5S), 624–643.

Shen, L., Margolies, L. R., Rothstein, J. H., Fluder, E., McBride, R., & Sieh, W. (2019). Deep Learning to Improve Breast Cancer Detection on Screening Mammography. *Scientific Reports*, *9*(1), 12495. https://doi.org/10.1038/s41598-019-48995-4

Vijayalakshmi, S., Pandey, B. K., Pandey, D., & Lelisho, M. E. (2025). Innovative deep learning classifiers for breast cancer detection through hybrid feature extraction techniques. *Scientific Reports*, *15*(1), 22212. https://doi.org/10.1038/s41598-025-06669-4

World Health Organization. (2025, August 14). *Breast cancer*. WHO - World Health Organization. https://www.who.int/news-room/fact-sheets/detail/breast-cancer

Zhang, W., Wang, F., Zhu, L., & Zhou, Z. (2014). Corner detection using Gabor filters. *IET Image Processing*, *8*(11), 639–646.