Research Article

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A data augmentation approach to enhance breast cancer detection using generative adversarial and artificial neural networks

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Abstract: Breast cancer is globally known to be a major health concern that necessitates advancements in detection and classification methods. This study introduces a machine learning-based approach for breast cancer diagnosis using benign and malignant mammograms of breast cancer. A two-hidden-layer artificial neural network (ANN) model was designed to categorize breast cancer from mammographic images. Prior to analysis, the images were subjected to a sophisticated data augmentation process that leveraged data denoising, contrast enhancement, and the application of a generative adversarial network (GAN). This multi-enhancement preprocessing enriched the quality of the images and transformed them into a format more amenable to analysis by vectorizing the pixel data. The methodology involved rigorous training of the ANN on input images, resulting in a significant improvement in the model's ability to classify breast cancer accurately. Experimental results demonstrate a notable enhancement in classification performance, with an increase in accuracy ranging from 22.5 to 42.5% compared to traditional scans. The final model achieved an impressive accuracy rate of unity, which considered all stages of image processing, including normal, contrast-enhanced, denoised, and GAN-enhanced scans. The outcomes of this research underlined the effectiveness of data augmentation and ANN in medical imaging. Future innovations in breast cancer diagnostics are elaborated by the potential to improve early detection and patient outcomes. The robust offered methodology for breast cancer detection is considered to be a significant contribution to biotechnological fields of interest.

Keywords: artificial neural network, breast cancer, cancer detection, data augmentation, generative adversarial network

1 The genesis and tapestry of research

1.1 Introduction

Breast cancer is characterized by the malignant growth of cells within the breast tissue and poses a significant health challenge worldwide [1,2]. It is a complex disease, often developing in the milk ducts or lobules, and has the potential to spread throughout the body [3,4]. Early detection is key to improving survival rates and mitigating the adverse effects of the disease. The urgency for precise and early diagnosis has propelled rapid advancements in medical imaging techniques, which play a pivotal role in monitoring and guiding treatment strategies [5]. However, despite the availability of various imaging methods, challenges persist in accurately distinguishing between benign and malignant cases. This complexity is further compounded by the variability in cellular presentation, such as differences in size, shape, and location within the breast tissue [6]. The need for a more accurate and efficient diagnostic approach is evident, as it can greatly enhance treatment outcomes, reduce patient discomfort, and potentially lower mortality rates. In the context of breast cancer research, the exploration of the interplay between hormonal factors, genetics, and environmental influences continues to be of paramount importance.

The traditional techniques for breast cancer detection, primarily mammography and biopsy, each have their limitations and complexities. Mammography is widely used for early detection but faces challenges in accurately

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identifying cancerous tissues, especially in dense breast tissue [7,8]. Biopsy, on the other hand, provides a more definitive diagnosis but carries risks associated with invasive procedures [9,10]. The variability in mammographic interpretation and the invasive nature of biopsies necessitate the development of more sophisticated and non-invasive diagnostic tools. Deep learning (DL), which is known to be a subset of machine learning, offers a promising avenue in this regard. It has the potential to revolutionize breast cancer detection by learning directly from image data, thereby enhancing accuracy and efficiency in diagnosis. This study introduces a novel machine learning-based approach that utilizes a two-hidden-layer neural network model trained on an enriched dataset through advanced image processing techniques of data augmentation, namely data denoising, contrast enhancement, and generative adversarial network (GAN) applications. The integration of these methods aims to address the inherent challenges in breast cancer diagnosis and the limitations of small datasets, which offer more reliability and automated solutions for the early detection and classification of this prevalent disease.

1.2 Literature review

A recent study has proposed a two-stage model for breast cancer detection using thermographic images [11]. The approach is notable for its use of the VGG16 DL model combined with an optimized Dragonfly Algorithm. The innovation in the work lies in the incorporation of the Grunwald–Letnikov (GL) method to enhance the performance of the Dragonfly Algorithm. The model was evaluated using the DMR-IR standard dataset and demonstrated an impressive 100% diagnostic accuracy. A significant achievement of the model is its ability to reduce the feature set by 82% compared to the VGG16 model alone, showcasing efficiency in feature selection and potentially faster processing times. Another study has investigated the effectiveness of various DL architectures by leveraging transfer learning for breast cancer detection in histopathological images [12]. The work stands out for its use of multiple advanced architectures, including ResNet, ResNeXt, SENet, Dual Path Net, DenseNet, NASNet, and Wide ResNet. Utilizing the BreaKHis database of 7,909 histopathological images, the study demonstrated high accuracy rates, with the best models achieving up to 99.8% accuracy. The study emphasized the power of transfer learning in adapting non-specific DL models to highly specialized tasks like breast cancer detection. The automatic classification of breast cancer using histopathological images was a central focus in the study of Buvaneswari *et al.* [13]. The method involved preprocessing for noise removal and image resizing, then feature extraction using a 3D-convolutional neural network. The classification was performed using stochastic diffusion kernel recursive NNs (SDKRNN). The model was tested across various datasets, yielding a balanced set of performance metrics, including 98% accuracy and an F-1 score of 89%. A previous study compared six in-tuned DL models using transfer learning for breast tumor classification [14]. The study introduced a custom model trained on a public dataset with results showing that the models trained on the augmented dataset with 7,800 images had achieved up to 98.11% accuracy. Moreover, a novel approach for breast cancer detection using ensemble DL architectures integrated with the Web of Things (WoT) was presented in the study of Sheeba *et al.* [15]. The methodology involved collecting input images through WoT, preprocessing with Gaussian filtering, and segmentation using active contour convolutional neural networks. This study led to a high classification accuracy of 96% and a detection accuracy of 92%. The results showed the potential of combining DL with emerging technologies like WoT for enhanced breast cancer detection. Table 1 lists a simply comprehensive presentation of the comparison between the five cited papers.

1.3 Research gap and contribution statement

Despite the advancements highlighted in the referenced studies, there remains a significant research gap in the integration and optimization of machine learning techniques for the analysis of diverse image types in breast cancer detection. Current methodologies primarily focus on single-type image analysis (thermographic, histopathological, ultrasound, or microscopic) and often employ conventional DL models without fully exploiting the potential of data augmentation and hybrid algorithmic approaches. The present study introduces a novel machine learning-based architecture that not only bridges this gap but also brings a new perspective to the field. This study employs a two-hidden-layer neural network model optimized through a comprehensive data augmentation process involving denoised data, contrast-enhanced images, and the use of a GAN. This approach allows for the effective processing of a diverse range of image types, thereby enhancing the model's accuracy and generalizability. Furthermore, the model's ability to efficiently vectorize images and handle complex datasets sets it apart from existing methods, offering a more robust and versatile solution for early and accurate detection of breast cancer across different imaging modalities. This innovation not only fills the identified research gap but also marks a significant step forward in the application of DL in medical imaging.

2 Developed methodology

In this study, the proposal of a marginally novel machine learning-based methodology for the classification and detection of breast cancer is given. The current approach advances such classifications by leveraging the strengths of the utilized artificial neural network (ANN) model. Generally speaking, the approach is primarily focused on processing mammographic images, which are inherently complex and require a sophisticated analysis technique to ensure accurate diagnosis. The dataset employed in the present research was acquired from a publicly available source, as mentioned in the study of Deb *et al.* [16]. The link to freely access the open-source data is available at the following portal: https://github.com/sagardeepdeb/rahman_xception_global, where all the scans are presented. It comprises mammographic scans of varying resolutions, predominantly larger than 4,000 × 2,000 pixels. To maintain the integrity and quality of these high-resolution images, regions of interest (ROIs) containing the mass were meticulously extracted rather than resizing the entire mammograms. Examples of these ROIs, both benign and malignant, post-preprocessing, are integral to the proposed analysis. For visual reference, representative mammographic scans from the dataset are depicted in Figure 1.

Computers are being utilized heavily in the field of biological medicine and other diagnostical approaches [17–20]. The methodology deviates from traditional approaches by utilizing a modified ANN, initially developed for image classification tasks. This network is particularly suited for deep feature extraction due to its inception modules, depthwise separable convolution layers and residual blocks. The modification lies in the enhancements of the ROIs before processing them into classification tests. To enhance the performance of the proposed model, the study adopted contrast-enhancing, denoising, and GAN image pre-processing techniques. These techniques aid in the more effective extraction of features, which is crucial for the subsequent classification process. The GAN process is particularly adept at emphasizing the most prominent features in the mammograms, which is essential for distinguishing between benign and malignant cases. Figure 2 elaborates on the workflow process of the presented approach, where the images are progressed through a two-hidden-layer ANN after the pixels are vectorized accordingly.

Table 1: Literature survey of currently applied state-of-the-art methodologies

Ref.	Methodology used	Image type	Key techniques/algorithms	Dataset size	Performance metrics
[11]	Thermographic images	Thermographic	VGG16, Dragonfly Algorithm, GL method	Standard dataset	High accuracy with 82% fewer features
[12]	DL with transfer learning	Histopathological	ResNet, ResNeXt, SENet, Dual Path Net, DenseNet, NASNet, Wide ResNet	7,909 images from 82 patients	Up to 99.8% accuracy
[13]	Feature extraction and classification using DL	Histopathological	3D-CNN, SDKRNN	Various datasets	Accuracy: 98%, precision: 93.8%
[14]	Comparison of DL models using ultrasound images	Ultrasound	ResNet-50, Inception-V3, Inception-ResNet-V2, MobileNet-V2, VGG-16, DenseNet-121	780 images, augmented to 3,900 and 7,800	Up to 98.11% accuracy
[15]	DL techniques integrated with WoT for microscopic image analysis	Microscopic	Gaussian filtering, active contour CNN, and transfer learning with regional attention mechanism	Not specified	Detection accuracy: 92%, specificity: 91%

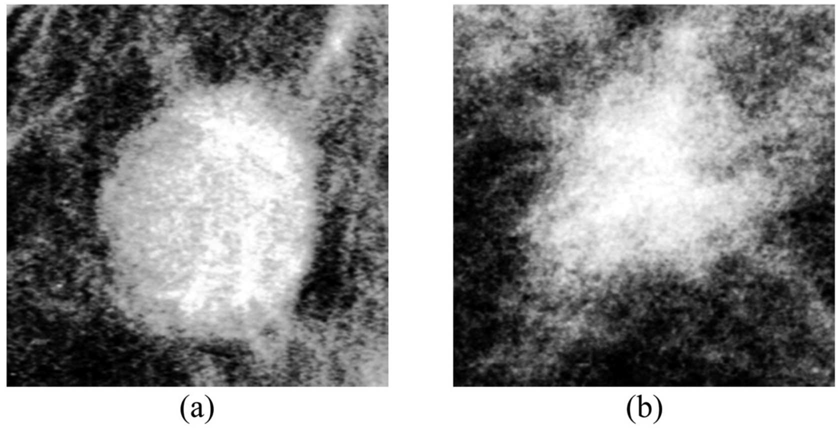

Figure 1: Acquired and randomly selected mammographic scans of breast cancer dataset: (a) benign and (b) malignant.

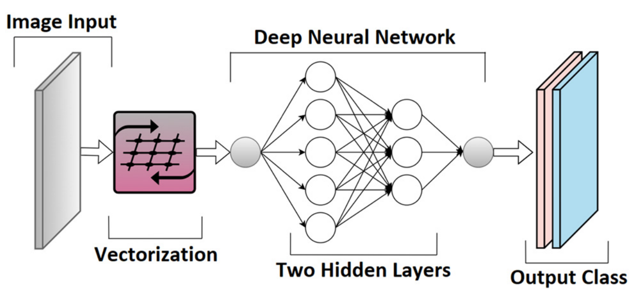

Figure 2: The workflow of the ANN-based image classifying methodology.

3 Theoretical basis

This section describes the data augmentation process in order to enhance the classification of breast cancer scans. This part of the research also delves into the procedure followed for creating the ANN.

3.1 Data augmentation

Data augmentation is a crucial process in the field of machine learning, which is particularly used for medical imaging. It involves artificially expanding the size and variability of datasets by altering the images in ways that are plausible during real-world usage. This study covers three key data augmentation methods which are contrast enhancement, image denoising, and GANs. First, contrast enhancement is used to improve the visual quality of images by increasing the contrast between the different features in an image. A common approach to contrast enhancement is histogram equalization, which modifies the intensity distribution of an image. The transformation function $T(r)$ can be defined as

$$T(r) = (L - 1)\int_{0}^{T} P_{\mathrm{r}}(w)\mathrm{d}w, \tag{1}$$

where r and $T(r)$ are the original and transformed intensities, respectively, L is the total number of possible intensity levels in the image, and $P_{\mathrm{r}}(w)$ is the probability density function of the pixel intensities. Moreover, as a second method, image denoising involves the removal of noise from the image while preserving important structural details. A simple yet effective method for denoising is Gaussian filtering. The Gaussian filter applies a convolution operation to each pixel with a kernel that represents a Gaussian distribution. The kernel $G(x, y)$ for a 2D Gaussian filter is given by

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}}, \tag{2}$$

where x and y are the distances from the origin in the horizontal and vertical axes, respectively, and σ is the standard deviation of the Gaussian distribution. Finally, GANs are used to generate new data samples that are indistinguishable from the original dataset. A GAN consists of two networks: a generator G and a discriminator D. The generator creates images while the discriminator evaluates them. The objective function of a GAN is formulated as

$$\begin{aligned} \mathrm{Min}_G \mathrm{Max}_D V(G, D) &= \mathbb{E}_{x\sim p_{\mathrm{data}}}[\log (D(x))] \\ &\quad + \mathbb{E}_{y\sim p_{\mathrm{g}}}[\log (1 - D(y))] \\ &= \int_{x\in\chi} p_{\mathrm{data}}(x)\log(D(x)) \\ &\quad + p_{\mathrm{g}}(x)\log(1 - D(x))\mathrm{d}x. \end{aligned} \tag{3}$$

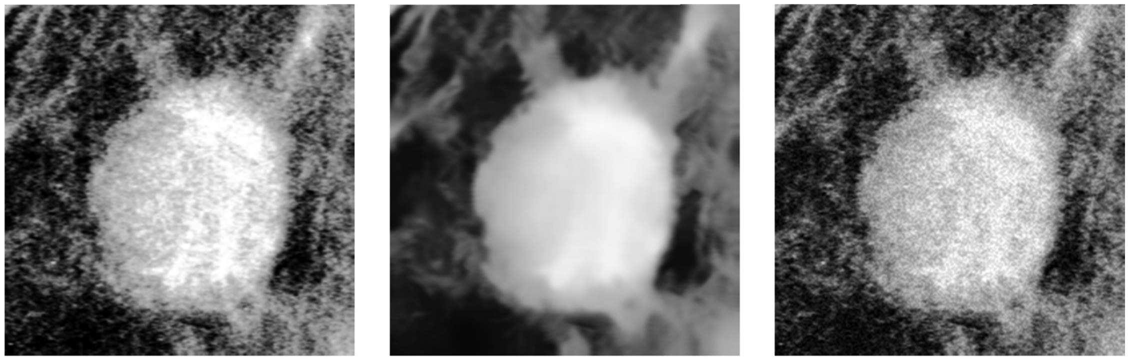

Figure 3: Enhanced benign mammographic scans of breast cancer: (a) contrasted, (b) denoised, and (c) GAN analysis.

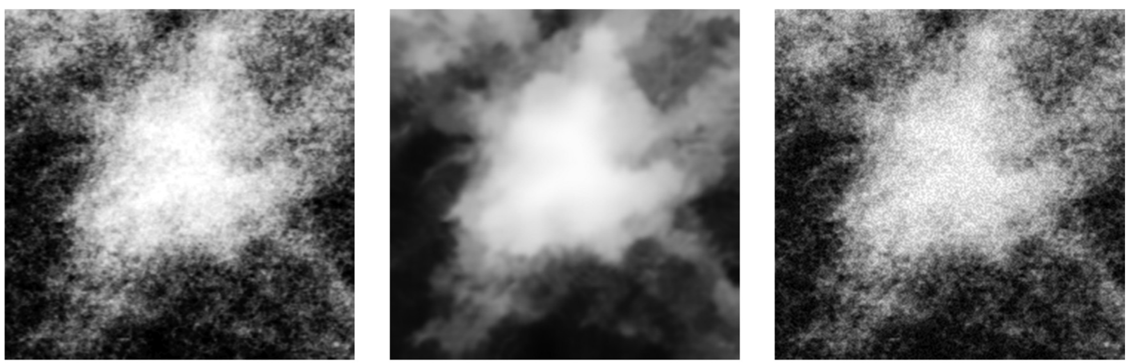

Figure 4: Enhanced malignant mammographic breast cancer scans: (a) contrast-enhanced, (b) denoised approach, and (c) GAN analysis.

Here, x is a real image from the dataset, z is a noise vector, p_{data} is the data distribution, p_g is the noise distribution, $G(z)$ is the generated image, and $D(x)$ is the discriminator's estimate of the probability that x is a real image. Figures 3 and 4 display the results of the three methods for both the benign and malignant breast cancer scans, respectively.

3.2 ANN

Machine learning has proven to be effective in many different applications, regardless of the required regression or classification purposes [21–32]. An ANN is a computational model inspired by the way biological neural networks in the human brain process information [33,34]. It is composed of interconnected nodes or neurons, which process data and pass it through layers to produce an output [35]. The basic operation of a neuron in an ANN, the adopted activation function [35], and the stochastic gradient descent (SGD) solver [30,36] can described by the following equations:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right), \tag{4}$$

$$f = \tanh(x) = \frac{\sinh(x)}{\cosh(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}}, \tag{5}$$

$$w_{\text{new}} = w_{\text{old}} - \eta \nabla Q(w_{\text{old}}, x_i, y_i), \tag{6}$$

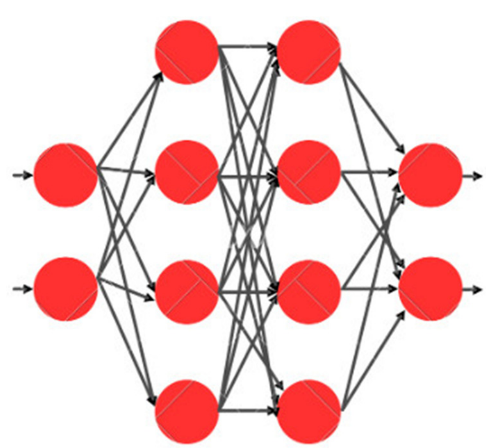

Figure 5: The utilized ANN structure.

Table 2: Parameter values of the adopted ANN model

Parameter	No. of hidden layers	No. of neurons in the first layer	No. of neurons in the second layer	Solver	No. of iterations
Value	2	4	4	SGD	1,000

where y is the output, x_i are the inputs, w_i are the weights, b is the bias, and f is the activation function. This mathematical formulation allows ANNs to learn complex patterns and relationships within data, making them highly effective for tasks like image classification and pattern recognition. Figure 5 depicts the adopted ANN structure, while Table 2 enlists the parameters for progressing the images.

4 Results and discussion

In terms of discussing the results, it is important to point out that after the data were extracted from the images, it was turned to numerical features. The numeric value corresponds to the letter n, where the methodology has extracted countless numerical values of around 2,500.

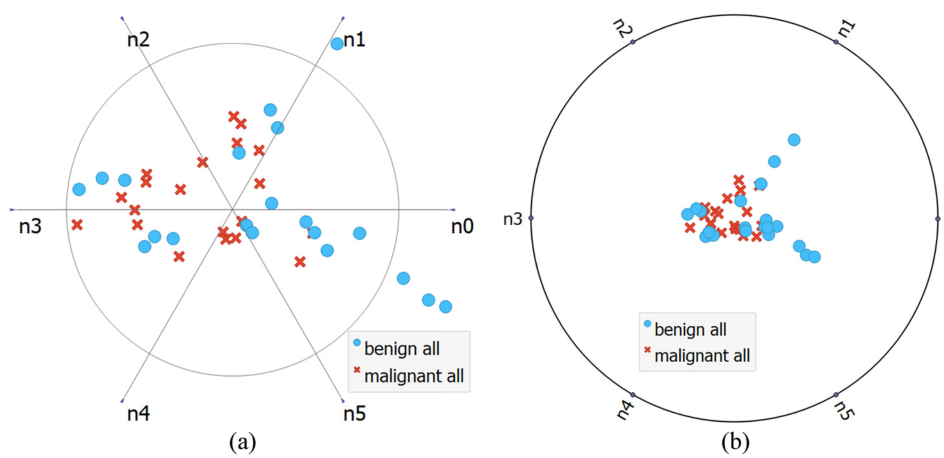

Figure 6: Visualization of the trained data: (a) free and (b) radial.

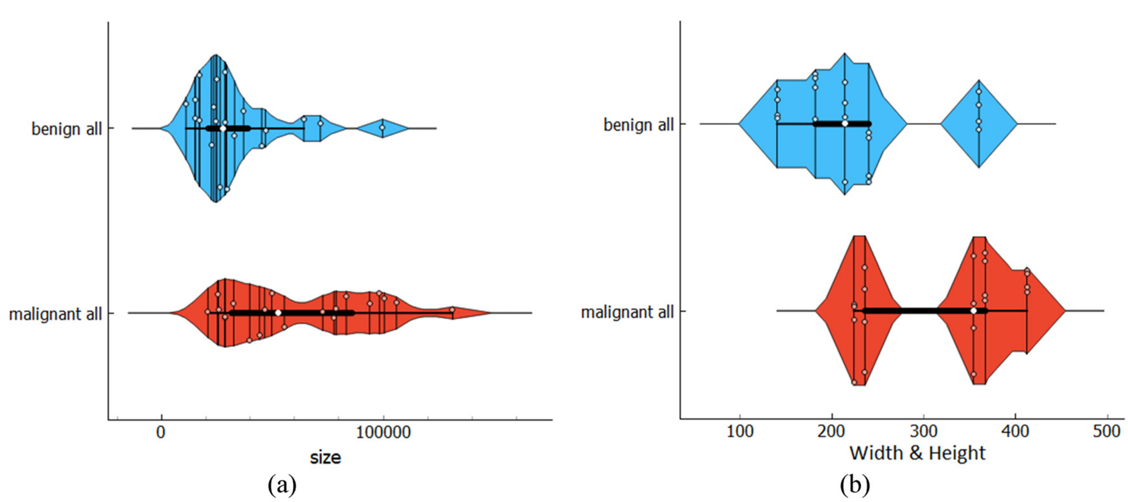

Figure 7: Violin plot of the three features: (a) size and (b) width and height.

Table 3: Classification-based results

Test dataset	Result accuracy of classification (%)
Normal	57.5
Denoised	65.0
Contrast Enhanced	77.5
GAN	100

These statistics are based upon three main features, namely the size, width, and height of the image. Although some approaches would conduct important selection techniques, this current approach is to advance them for classification purposes. The first three numerical results ($n0$–$n5$) are randomly selected for depiction in Figure 6. Figure 6a visualizes the free depiction of the trained dataset scans of benign and malignant while corresponding to the five true numerical statistics. While the radial visualization is depicted in Figure 6b, it is concluded that $n1$ is a feature where it classifies benign tests easily, while $n2$ corresponds more to the malignant scans. Moreover, the violin plots for the three main features are illustrated in Figure 7. The size feature is shown in Figure 7a where it can be seen that the malignant scans are of higher diversity, which makes it a hard challenge for classification. Figure 7b, on the other hand, depicts the width violins while pointing out that the height is of the same instances because all the scans are cropped on the same width and height.

The classification results of all three methods, in addition to traditional datasets, are listed in Table 3, where the recognition accuracy is presented in percentages. Corresponding to this, the confusion matrix for each of the overall four techniques is elaborated upon in Figure 8. The testing dataset comprises 40 total images where half of which correspond to malignant scans, and the others are healthy. When the normal image scans were progressed into the ANN model, 57.5% was predicted correctly with 7 only identifying as malignant where 2 were wrong. This is an absolutely not dependable prediction methodology with high percentages of error. The denoised dataset, on the other hand, was of marginally similar results with a classification accuracy of 65%. Following up, the contrast-enhanced group of images was slightly better in prediction, with a recognition accuracy of 77.5%. However, this cannot be trusted among medical applications, which require a classifying near perfection. Interestingly, the proposed GAN-enhanced dataset had exhibited a remarkable classification accuracy which exceeded expectations with a value of unity. GANs can be advantageous over normal images because they have the capability to generate synthetic images; in addition, GANs could potentially handle noise in a more adaptive and dynamic way during the generation process. It is also concluded that the synthetic images produced by GANs might exhibit better contrasts and highlight relevant features for improved classification. While GANs might not bring such advantageous results in

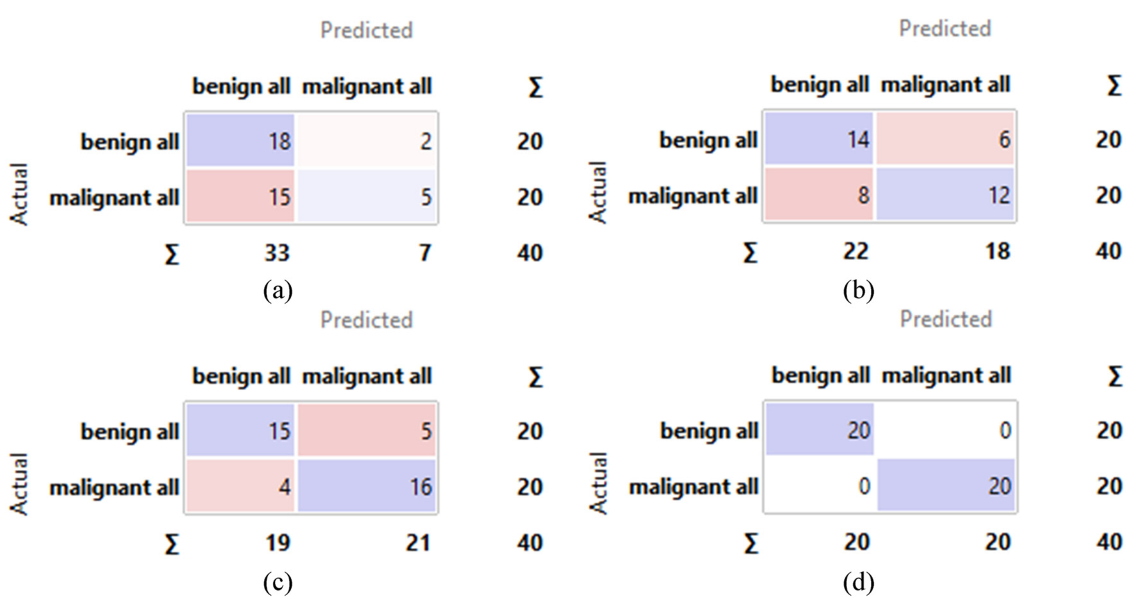

Figure 8: Confusion matrix for each of the four tested datasets: (a) normal scans, (b) denoised, (c) contrast-enhanced dataset, and (d) GAN.

other fields of operation, it is concluded that GANs work perfectly when used for breast cancer scan classification.

5 Conclusion

In conclusion, this study presented a robust machine learning-based approach for breast cancer diagnosis by leveraging a two-hidden-layer ANN model and a comprehensive data augmentation process. The incorporation of data denoising, contrast enhancement, and GAN techniques has significantly improved the quality of mammographic image classification. It led to a remarkable accuracy rate of 100% in the final model of which GAN-based enhancements were adopted. The detailed analysis of numerical features extracted from images, namely nx, highlighted the importance of considering size, width, and height for classification purposes. Notably, GAN-enhanced datasets demonstrated superior performance compared to normal, denoised, and contrast-enhanced images, showcasing the potential of GANs in generating synthetic images with improved contrasts for accurate breast cancer classification. This research contributes significantly to the biotechnological field by emphasizing the efficacy of data augmentation and ANN in medical imaging, particularly in the context of breast cancer diagnostics and computers in biotechnology. The findings also underscored the potentiality of future innovations to enhance early detection and improve patient outcomes in bio-related fields of breast cancer diagnosis and image processing.

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Conflict of interest: The authors state no conflict of interest.

Data availability statement: The image dataset referenced from article [16] was used as a foundation for applying the new methodologies introduced in this study. However, all newly generated data, including images and results, are original and fully presented in this manuscript.

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