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# Amalgamation of GAN and ResNet methods in accurate detection of Breast Cancer with Histopathological Images

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**Abstract**

***Breast cancer analysis is critical for clinical diagnosis and treatment because of its association with abnormal cell growth and tumor formation, which pose a significant health concern among women. Researchers have extensively explored traditional and individual deep learning algorithms, such as convolutional neural networks (CNNs) and artificial neural networks (ANNs), for this purpose. However, reliance on mono-based models often results in suboptimal classification accuracy in medical diagnosis. To get around this problem, we suggest a new method that combines generative adversarial networks (GANs) and residual neural networks (ResNets) in a way that works well together to accurately find breast cancer in histopathological images. Our approach leverages an enriched dataset to ensure better generalization during training. We employ GANs to augment the training dataset by generating synthetic images, which enhances feature recognition and improves the robustness of the model. We then use this augmented data to fine-tune ResNet, a robust deep learning architecture, for classification tasks. The GAN-ResNet framework uses discriminatory features taken from the generated images by the GAN discriminator. This combines the power of GANs for discrimination with the power of ResNet for classification. We specifically fine-tuned the final model layer for binary classification, enabling accurate differentiation between malignant and benign breast tissue. Additionally, we adapted the loss function to address imbalances in the medical dataset, ensuring a more robust and accurate model. Our proposed model demonstrates a remarkable 98% accuracy in analyzing histopathological images, validating its efficacy for early breast cancer detection. This innovative approach underscores its potential for significant advancements in clinical diagnostics. This version highlights the novelty of combining GANs with ResNet and emphasizes the unique aspects of your approach, such as the use of synthetic images for data augmentation and the adaptation of the loss function to handle dataset imbalances.***

**Keywords**: Breast cancer detection, GAN, Residual Neural Networks, Convolutional Neural Networks, Machine Learning.

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# 1 Introduction

Breast cancer is a worldwide health concern that affects millions of women. According to the World Health Organization (WHO), breast cancer caused 685,000 deaths globally in 2020. Breast cancer is the most commonly diagnosed cancer type, accounting for 1 in 8 cancer diagnoses worldwide (26). Breast cancer is a complex disease, and its exact cause is not known. Certain factors, however, increase the risk of developing breast cancer. Lifestyle factors such as alcohol consumption, poor diet, physical inactivity, and obesity. Similarly, genetic factors and a family history of cancer can inherently have an impact on an individual (14; 29). A tumor is defined as an abnormal growth of a tissue that serves no specific purpose. This allows the cells in the body to grow quickly and behave differently based on whether the tumor is benign (non-cancerous) or malignant (cancerous).

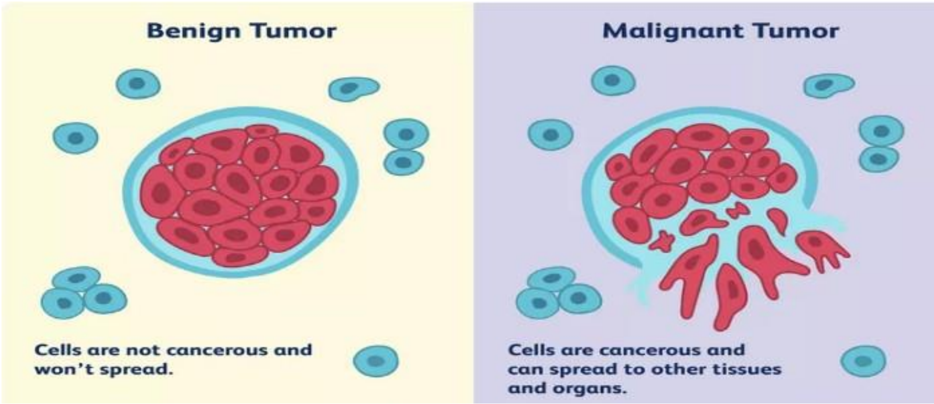



**Fig. 1.** Image of a Benign and Malignant tumor

Figure 1 explains the representation of benign and malignant tumors. Benign tumors do not harm any other tissues in the body and are distinct from the surrounding cells. Cancer cells that are abnormal and behave differently from the remaining or nearby tissues form malignant tumors, which grow uncontrollably and invade nearby tissues. Malignant tumors, which are cancerous, can be present anywhere in the body. This paper investigates the early detection of breast cancer, and the classification is based on the specific cell types involved in the disease's development. Anatomically, the breast consists of milk-producing glands located anteriorly to the chest wall, resting upon the pectoralis major muscle, with supporting ligaments connecting the breast to the chest wall. The breast comprises 15 to 20 lobes arranged in a circular fashion. The fatty tissue enveloping the lobes influences the size and shape of the breast.

Figure 2 above illustrates the exponential growth in breast cancer over the years, highlighting a significant study that requires careful analysis and diagnosis. Early detection of breast cancer can improve the prognosis and significantly increase survival rates. In addition, the accurate classification of benign tumors can prevent patients from undergoing unnecessary treatments. Thus, the correct diagnosis of breast cancer and classification of cancer patients in terms of either a malignant or benign group is the subject of much research. Deep learning methods are an effective way to classify data, and they have the advantage of critical feature analysis over the cancer data set.

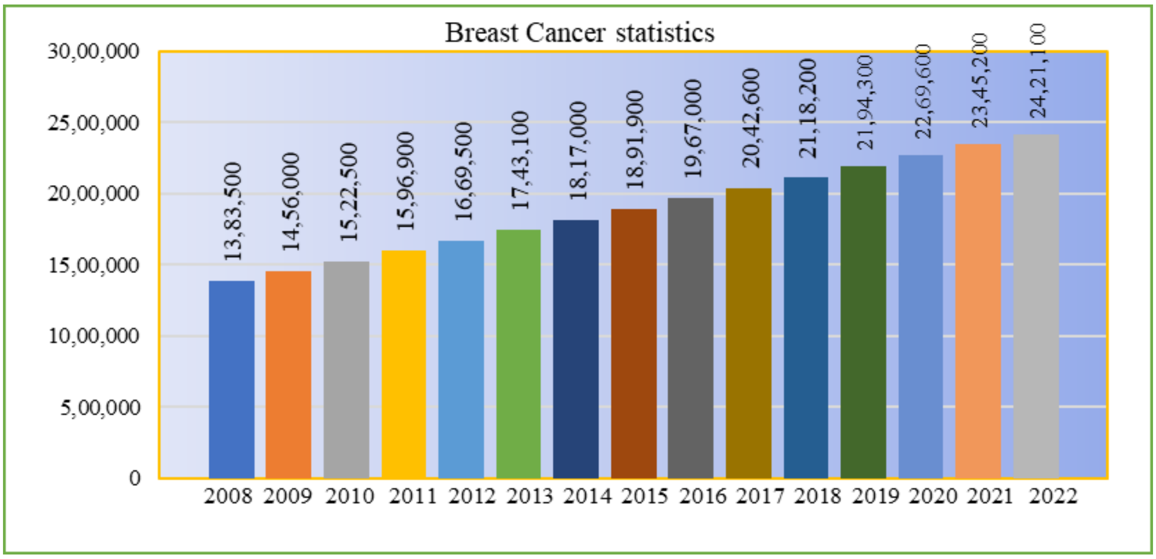



**Fig. 2.** 15-yearWHO breast cancer statistics

The medical field extensively employs these methods for diagnosis and analysis. Lobules within each lobe contain hormone-activated glands for milk production. Breast cancer typically develops without noticeable symptoms. People often become aware of the disease during routine screening procedures. Breast cancer is the most common cancer diagnosed in women, accounting for over 10% of new cancer cases each year. Globally, it ranks as the second-leading cause of cancer-related fatalities among women. Breast cancer risk factors encompass seven broad categories, such as age, gender, personal history of breast cancer, histologic risk factors, family history of breast cancer and genetic factors, reproductive risk factors, exogenous hormone use (28; 12) etc. Breast cancer can manifest a variety of symptoms, particularly in advanced stages, while early-stage cases may often present with no noticeable signs. Potential symptoms of breast cancer include breast lumps or thinning, which is often painful; sudden changes in size, shape, or appearance of the breast; skin alterations; nipple changes; and abnormal fluid from nipple decisions. Additionally, it aids in pinpointing subtle clues and early indications of illnesses, furnishing healthcare practitioners with crucial information for enhanced and prompt diagnosis through a more effective and accurate method of disease identification and observation. Other authors have explored deep learning techniques using histopathological images, providing valuable insights in the field of pathology. Several approaches exist, such as convolutional neural networks (CNNs) (5), transfer learning (24), recurrent neural networks (2), residual networks (18), and generative adversarial networks (10).

By harnessing the Collaborative Fusion Framework strengths of these three components, the Combined Force model aims to create a robust and accurate breast cancer detection system. The CNN captures intricate patterns, the ResNet ensures efficient training of deep networks, and the GAN enhances the diversity and richness of the dataset. This collaborative approach strives to improve the sensitivity and specificity of breast cancer detection algorithms, ultimately benefiting early diagnosis and patient outcomes. This study's central objective is to detect breast cancer from histopathological images. To achieve this, we investigate the GAN and ResNet models. This study's significance could contribute to efficient breast cancer detection and improved patient outcomes. To carry out our work effectively, we require the following contributions:

- Perform the feature extraction using GANs, and combine these extracted features with a ResNet architecture for breast cancer analysis.
- To adjust the hyperparameters and examine various data preprocessing techniques, with a particular focus on datasets that experienced adaptive equalization preprocessing and those that did not.
- During the model's training phase, experiment with various optimizers to identify the most efficient one.
- To evaluate the proposed method using a variety of metrics, including accuracy and loss performance scores.

## 2 Related Work

Artificial intelligence (AI) is heralding a promising future for breast cancer detection, bringing about transformative advancements in accuracy, efficiency, and early diagnosis. This field of technology holds the potential to revolutionize how we approach breast cancer screening and diagnosis, offering several benefits. (4) ResNet-50 belongs to the ResNet family and stands out with a depth of 50 layers. This model's architecture draws inspiration from the concept of residual learning. The inclusion of residual blocks addresses common problems in CNNs, such as gradient disappearance and model degradation. This innovation enables the construction of extremely deep neural networks, facilitating more efficient training and optimization processes. In (16), researchers introduced a novel approach based on transfer learning to classify breast histology images into four distinct subtypes: normal, benign, carcinoma in situ, and invasive carcinoma. The methodology involved normalizing histology images and fine-tuning two prominent convolutional neural networks, namely Google's Inception-V3 and ResNet50. This fine-tuning process utilized image patches to enhance the models' capability for accurate classification. This proposed method specifically employed the ResNet50 network for conducting test classifications. They (30) designed a framework for the automatic detection of breast cancer, utilizing a combination of transfer learning and augmentation strategies. In experiments conducted on the MIAS dataset, the system, utilizing ResNet50, demonstrated a notable accuracy of 89.5%. This approach signifies the potential efficacy of integrating transfer learning and augmentation techniques for enhanced breast cancer detection. In (1), researchers proposed an innovative approach that uses CNN-based transfer learning to detect breast cancer in mammography images, specifically within the domain of DL methods. This model demonstrated an impressive accuracy of 95.71% on the mini-dataset, surpassing the performance of other existing methods. We addressed the common challenge of class imbalance in breast cancer image classification, which typically limits the number of malignant samples compared to benign samples, and emphasized the potential bias during training. They incorporated an attention mechanism into their method to mitigate this bias, aiming to direct the model's focus to image regions crucial for classification. This attention mechanism improved the recognition accuracy of malignant samples, contributing to more robust and precise breast cancer detection. (33) Cycle-consistent GANs have shown remarkable efficacy in image-to-image translation tasks. Our investigation delves into whether cycle-consistent GANs can effectively transform a non-cancerous image into a cancerous image and vice versa, serving the purpose of data augmentation. The goal of this method is to use GANs to create fake images that look like both cancerous and non-cancerous situations. This will make the dataset more diverse and rich, which will help train and test the model more effectively. CNNs incorporate at least one convolution layer, which substitutes the traditional matrix multiplication with a convolution operation on the input matrix. We utilize this unique operation to extract both low-level and high-level features visible in the image. This helps the network learn and shows the complex patterns that are in the visual data (34). CNNs have the ability to acquire a larger number of features by expanding the network's depth. However, increasing the network's depth introduces challenges such as vanishing gradients and degradation (27). These issues can impede the effective training and optimization of the network, limiting its ability to learn and generalize well to complex tasks. We have introduced techniques like skip connections and residual learning to mitigate these problems and enable successful training of deeper networks. A framework led to a more straightforward optimization of the network, resulting in higher accuracy (20). The network, later recognized as ResNet, served as the foundation for entries in the ILSVRC competition. It achieved the first-place position in both the ImageNet detection and ImageNet localization tasks, showcasing its exceptional performance and effectiveness in large-scale image recognition challenges. In this context (15), certain researchers have focused on nuclei analysis, extracting features from nuclei to offer crucial information for the classification of cells into benign and malignant categories. This method stresses how important it is to use information from nuclei to improve the precision and usefulness of classifying cells in medical settings, especially when telling the difference between healthy and unhealthy cells. Similarly, researchers use clustering-based algorithms, the circular Hough transform, and various statistical features to segment and classify nuclei (19; 22; 13). In the realm of medical image analysis, algorithms designed for histopathological images are advancing rapidly. However (17; 32), there remains a substantial demand for an automatic system that can deliver efficient and highly accurate results. The ongoing development in this field underscores the necessity for automated solutions to streamline the analysis of histopathological images, ensuring both efficiency and precision in medical diagnostics and research. This innovative approach aims to extract information directly from raw images, optimizing its utilization for classification processes. DL techniques, especially DNNs, have shown a lot of promise in automatically learning hierarchical representations from complex data. This makes tasks like image classification and feature extraction more accurate (25; 23). CNN has done well in areas of biomedical image analysis, including finding mitosis cells in microscopic images, tumors, dividing neural membranes into segments, skin disease classification, immune cell detection and classification, and mammogram mass (3; 8; 9; Ciresan et al. ; 6; 11). Multiple CNN architectures enhance learning performance and replace traditional single-model CNN architectures. Similarly, ImageNet pre-trains the combination of ResNet50, InceptionV2, and InceptionV3 to produce a rapid and accurate model for cell-based image classification.

Most of the previously mentioned works primarily focused on employing a mono-based model implementation, with little emphasis on using a fusion-based approach. The combined GAN and ResNet would help us get better beneficiary-informed results. We conducted the experiment in detail, and the upcoming sections on methodology and results will discuss its results.

## 3 Methodology

Breast cancer, a condition characterized by abnormal cell growth in the breast tissue, often eludes early detection due to its subtle symptoms. Deep learning, particularly the application of convolutional neural networks (CNNs) and generative adversarial networks (GANs), has emerged as a revolutionary tool in medical analysis, providing a new avenue for the automated examination of breast images. The integration of these cutting-edge techniques for breast cancer detection represents a significant advancement over conventional detection methods, enabling greater accuracy and earlier identification of the disease.

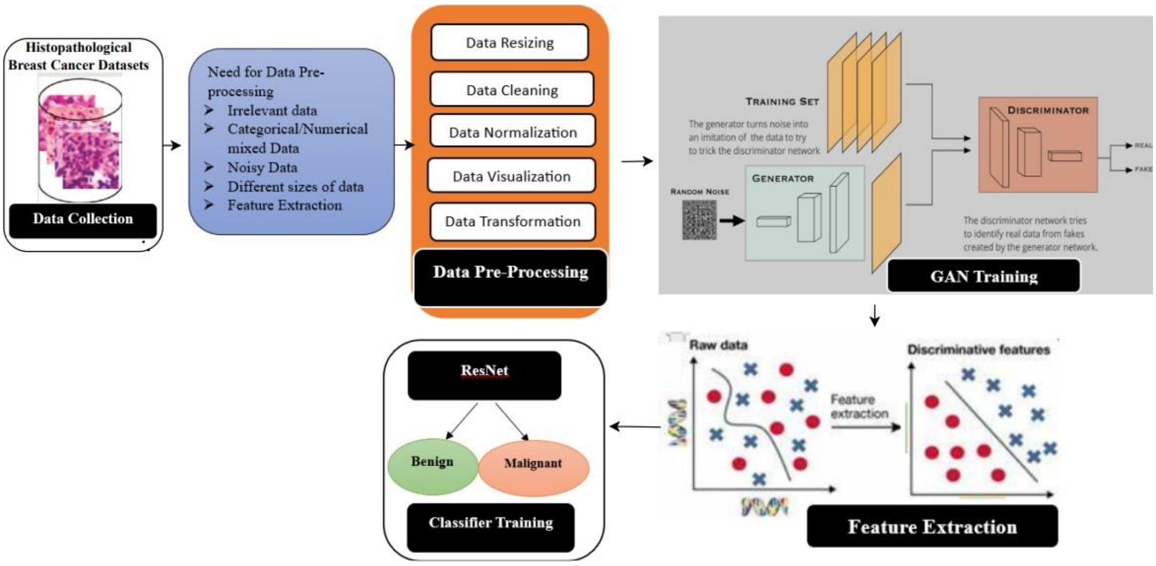



**Fig. 3.** Proposed System Architecture

Figure 3 illustrates the proposed system architecture workflow framework for breast cancer detection that utilizes generative adversarial algorithms. Networks (GANs) involve the below steps: **Data Collection:** We should label the large dataset of breast images, which includes both normal and cancerous tissues, to indicate whether or not they contain cancerous cells.

**Data Preprocessing:** We preprocess the images to standardize their size, resolution, and color. This involves augmentation techniques to increase the diversity of the dataset and improve the model's robustness.

**GAN Training:** Train a GAN architecture on the pre-processed dataset using two neural networks: a generator and a discriminator. The generator generates realistic breast images, while the discriminator exemplifies the difference between real and generated images.

**Feature Extraction:** The generator network extracts relevant features from the generated images. These features capture important characteristics of breast tissues that can aid in cancer detection.

**Classifier Training:** We apply a convolutional neural network-based classifier (ResNet) to the extracted features to classify images as either normal or cancerous. We evaluate the trained classifier's performance using a separate test dataset. We assess the model's effectiveness in detecting breast cancer using measures such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve.We validate the model's performance on additional datasets and adjust the parameters as needed to improve effectiveness and generalization.

**Deployment:** We use the trained model to analyze new breast images and provide predictions regarding the presence of cancerous cells, assisting healthcare professionals in making accurate diagnoses.

The effectiveness of augmentation techniques during data preprocessing is a significant consideration. When employing convolutional neural networks for categorizing images, it can pose a challenge to precisely determine the optimal methods for preparing images for analysis, such as adjusting or standardizing pixel values. Furthermore, we can use image data augmentation to boost the model's efficiency and reduce generalization errors. Incorporating augmentation techniques during testing can further refine the predictive capabilities of a trained model. Due to variations in size within the training dataset, images required resizing before integration into the model. Square images were adjusted to dimensions of 256×256 pixels, while rectangular ones were resized to have a minimum side length of 256 pixels, followed by extracting the central 256×256 square from the image. Training augmentation techniques enable the model to conform input images to a 224x224 shape. The acquired data originates from a variety of sources, but it is unorganized and requires tidying and preprocessing before analysis.

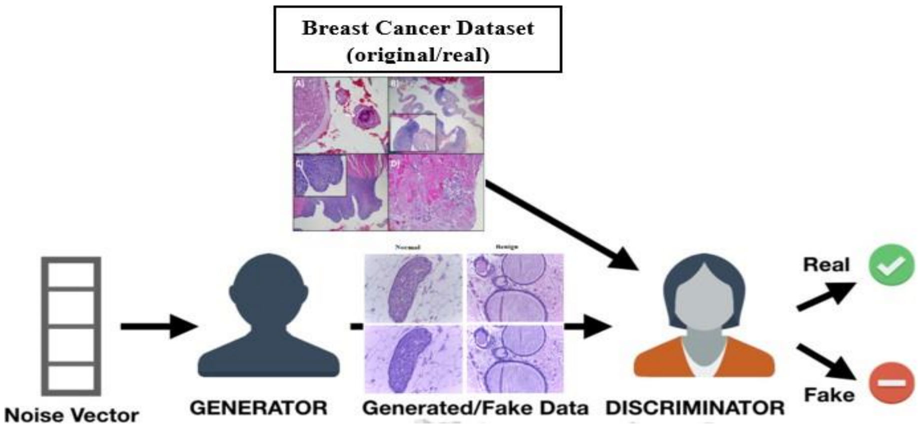



**Fig. 4.** The Generator and Discriminator of GAN applied on preprocessed data

The process involves cleansing the data, eliminating duplicates, and addressing missing values through imputation methods. After resizing, images undergo normalization, where normalizing pixel intensity values involves rescaling them to a specified range, typically between 0 and 1, which can enhance the effectiveness of machine learning algorithms. Data transformation refers to alterations made to the format or arrangement of data. Techniques such as smoothing and aggregation can mitigate noise within a dataset. Integration of data from diverse origins is essential; the significance of results is contingent upon the quantity and quality of the data. High data quality and quantity yield optimal outcomes. The pre-processed dataset, which uses the GAN framework, has a generator and a discriminator. The GAN methodology follows an iterative approach by alternating updates to the discriminator and generator. There are two types of loss functions that control the optimization process. The discriminator uses binary cross-entropy to maximize the log-likelihood of correct labels, and the generator loss is the opposite of the discriminator's confidence in synthetic images.

In this research, the GAN workflow consists of two primary components, as shown in Figure 4: the generator, responsible for generating similar images, and the discriminator, tasked with scrutinizing them. Not only does the discriminator play a crucial role in evaluating the generator's output, but it also serves as a powerful feature extractor for classification tasks. Upon achieving satisfactory performance with the GAN model, our attention shifted towards the discriminator's convolutional layers, renowned for their adeptness at detecting intricate patterns in breast cancer images. Leveraging these layers, we extracted feature maps that encapsulate the discriminator's response to various nuances within the input data. These feature maps manifest as two-dimensional matrices, wherein each element corresponds to the output of a filter applied at a specific location on the input image. These feature maps provide insights into the discriminator's ability to differentiate between normal and pathological structures. In a GAN setup, the discriminator distinguishes real from generated fake images. The extracted features reveal intricate patterns crucial for cancer detection, reflecting the model's decision-making process. By using ResNet's strong feature representation and skip connections that stop gradient vanishing, breast cancer classification is improved even more than the discriminator could do in the GAN method.

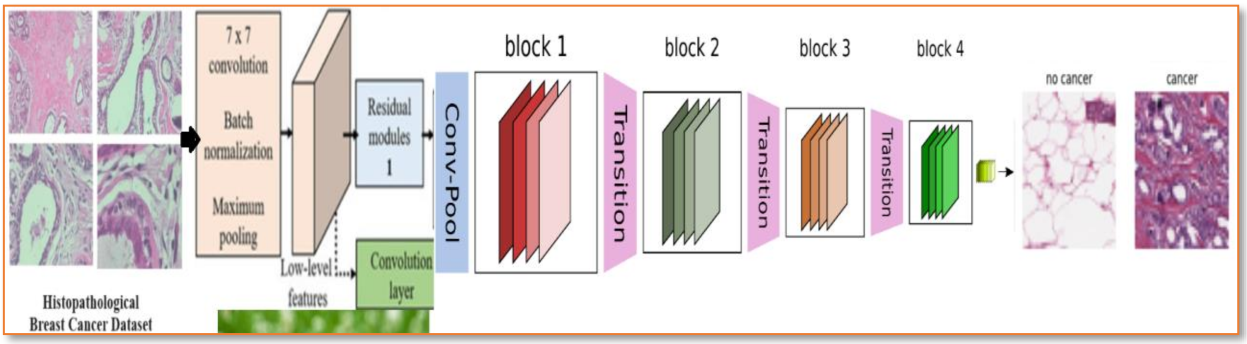



**Fig. 5.** Feature Extraction using RESNET

ResNet, which stands for "Residual Network," uses a 34-layer basic network structure that was based on VGG-19 from the Visual Geometry Group. Figure 5 illustrates the extraction of features using ResNet. This architecture incorporates shortcut connections, transforming it into a residual network. Two fundamental design principles guide the architecture: ensuring consistent output feature map sizes by maintaining the same number of filters across layers and maintaining time complexity per layer by doubling the number of filters when the feature map size is halved. The basic network integrates shortcut connections into its 34 weighted layers. When the input and output dimensions coincide, we directly apply identity shortcuts. We consider two approaches for increased dimensions: either we continue the identity mapping shortcut while padding extra zero entries, or we use a projection shortcut to align dimensions. Figure 6 shows the suggested method, which prepares the ResNet architecture on a large set of images and fine-tunes it using feature extraction from fundus images. This makes it more effective at extracting features from a wide range of ophthalmologic images. This fine-tuning process enables ResNet to adapt its pre-learned filters to the unique features present in these images. By adding the ResNet model to the feature extraction step of the GAN, we create a pipeline that starts with the GAN to add to the data and draw attention to important features.

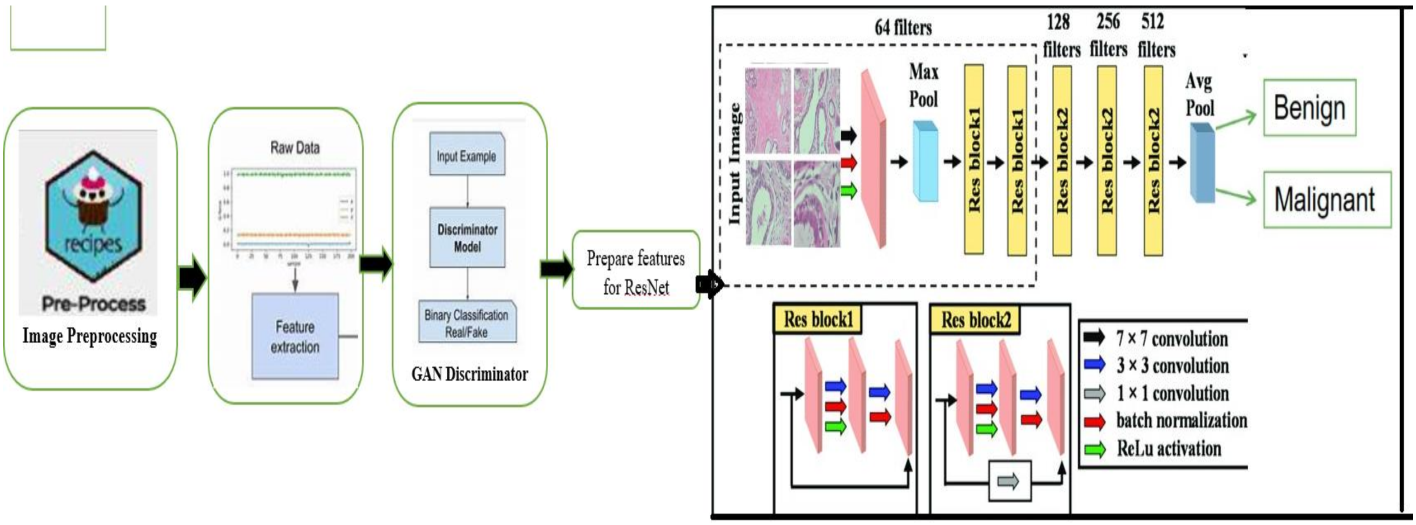
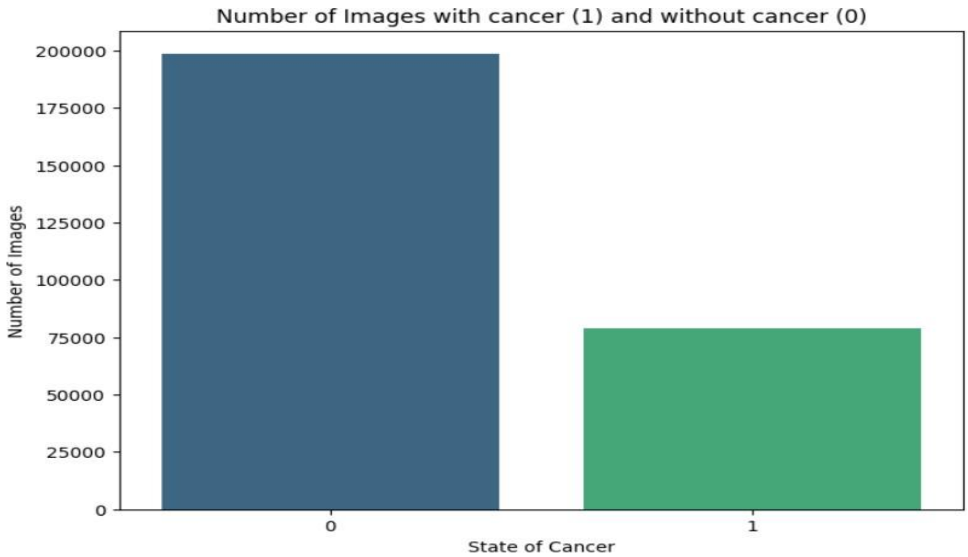



**Fig. 6.** GAN-ResNet Feature Integration Pipeline

Then, we use ResNet for high-precision classification, taking advantage of both the GAN's ability to combine and improve features that are specific to glaucoma and ResNet's skill in deep feature learning and abstraction. This combined GAN-ResNet workflow shows off the convolutional layers of the ResNet while also abstracting the GAN's feature extraction. This makes sure that the identification process doesn't just rely on raw pixel data but also includes retinal feature representations. Such abstraction proves crucial in identifying subtle patterns distinguishing between malignant and benign histopathological images. The ResNet's deeper layers and residual connections make it possible to train complex patterns without the risk of overfitting. This reduces some of the problems that are common with deep neural networks. During the final stages, we customize the classification layer of ResNet to distinguish between glaucoma and normal, healthy images. During the learning phase, a loss function optimizes the model's weights to account for the unequal distribution of classes. Within medical datasets, we ensure sensitivity to clinically significant but less prevalent cases, such as breast cancer images. The integrated GAN-ResNet model does a fantastic job of classifying breast cancer, as shown by a lot of testing and validation on a large dataset. The model's predictive accuracy stands as a reliable metric for detecting breast cancer at its initial stages, showcasing its potential for enhancing early diagnosis and intervention.

# 4 Results

For this study, we looked into a new deep learning architecture that uses the generative powers of generative adversarial networks (GANs) combined with ResNet to find breast cancer early in histopathological images. The developed model underwent comprehensive evaluation and comparison with traditional convolutional neural network architectures such as standalone GAN and ResNet-50. We applied the suggested method to a large dataset, supplemented it with GAN-generated samples, and modified it to include breast cancer in various stages. This made the training data more representative. a. After data augmentation, we fine-tuned ResNet on this expanded dataset, allowing the model to more effectively capture complex and simple patterns in breast cancer image representation. Furthermore, the proposed model demonstrated admirable consistency in evaluation, with testing accuracy ranging from 95.0% to 98.80%. This consistent performance suggests that the model not only effectively learned similar features but also maintained high reliability across various image presentations. This notable accuracy underscores the model's robustness and its capacity to generalize effectively to unseen or novel data. The GAN-ResNet model proposed in this study not only aimed to achieve high mean accuracy, but it also prioritized minimizing the variance between its minimum and maximum accuracies. This characteristic highlights the model's stability across the entire spectrum of the dataset. Maintaining such balance is particularly crucial in medical diagnosis tasks, where consistency is paramount for reliable decision-making. GAN classifies the images from the uploaded dataset into images with cancer and images without cancer by displaying the




count plot on the dataset regarding images with cancer as 1 and without cancer as 0, as shown in Figure 7.

**Fig. 7.** Displaying Count Plot on Dataset regarding images with cancer as 1 and without cancer as 0

Figure 8 illustrates the distribution of images according to pathology, and evaluates the image count based on properties such as spatial coverage, size, color, and texture.

GAN sorts the images based on specific attributes like breast density as part of the visualizing and data cleaning process. We collect a dataset containing histopathological images of breast tissue. These images may vary in terms of breast density, which is an important attribute in breast cancer diagnosis. We then employ the GAN to sort these images based on their breast density attribute. We visualize the dataset after sorting to understand the distribution of images across different breast density categories. We can utilize visualization techniques like scatter plots, histograms, or heatmaps to gain insights into the distribution and density of images within each category.

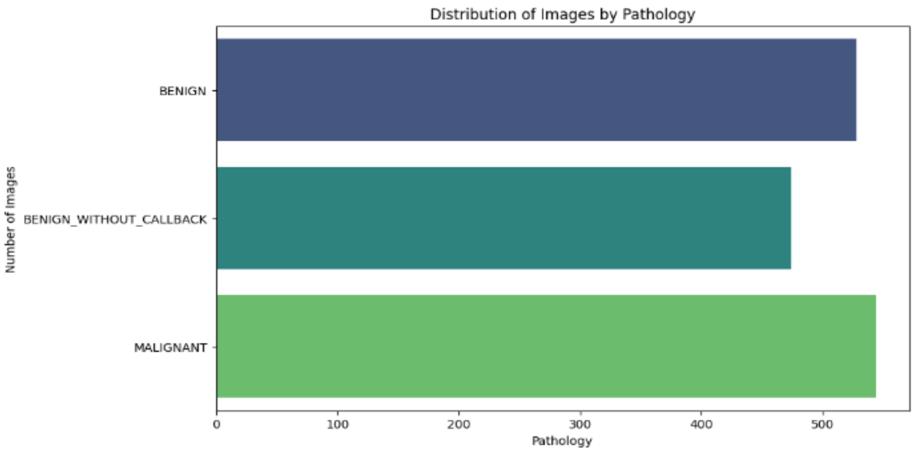



**Fig. 8.** Count on distribution of image properties

Figure 9 shows the distribution of images based on breast density using histogram visualization.

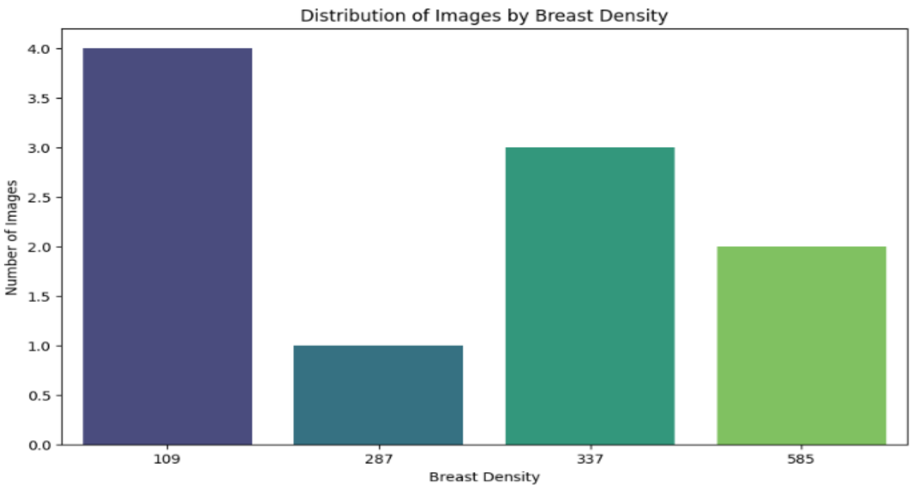



**Fig. 9.** Distribution of image based on breast density

This neural network model for image classification includes several layers: convolutional layers to detect features, batch normalization to stabilize training, ReLU activation for non-linearity, max pooling to reduce dimensions, and fully connected layers for final classification. The model uses a combination of these layers to learn complex patterns and achieve accurate predictions. It has a total of 308,323 parameters, with 307,171 being trainable, making it robust for tasks like detecting features in images. Table 1 explains the results of displaying the ResNet model summary at different layers in its hierarchical feature extraction process. The hyperparameters considered for the implementation of the neural network model are: activation layer, optimizer, learning rate, batch size, epochs, normalization, and dropout rate. This study demonstrates how the model refines and abstracts information as it progresses through its layers. These results not only facilitate model optimization but also aid in interpreting how different layers contribute to the overall predictive capability of the ResNet architecture. The optimal number of epochs that are considered for fine-tuning the training regimen strikes a balance between maximizing performance and preventing overtraining.

**Table 1.** This table summarizes the layers in the neural network model, including their types, output shapes, number of parameters, and a brief description of each layer's function

| Layer Type | Output Shape | Parameters | Description |
|---|---|---|---|
| Conv2D | (None, 25, 25, 64) | 9472 | Applies 64 filters to detect features like edges and textures. |
| BatchNormalization | (None, 25, 25, 64) | 256 | Normalizes the output to speed up training and improve stability. |
| Activation (ReLU) | (None, 25, 25, 64) | 0 | Introduces non-linearity to help the model learn complex patterns. |
| MaxPooling2D | (None, 13, 13, 64) | 0 | Reduces spatial dimensions to decrease computational load. |
| Conv2D | (None, 13, 13, 64) | 4160 | Further extracts features with 64 filters. |
| BatchNormalization | (None, 13, 13, 64) | 256 | Normalizes the output of the previous layer. |
| Activation (ReLU) | (None, 13, 13, 64) | 0 | Applies ReLU activation function. |
| Conv2D | (None, 13, 13, 64) | 36928 | Another convolutional layer with 64 filters. |
| BatchNormalization | (None, 13, 13, 64) | 256 | Normalizes the output of the previous layer. |
| Conv2D | (None, 26, 26, 3) | 771 | Applies 3 filters to the input. |
| AveragePooling2D | (None, 3, 3, 3) | 0 | Reduces dimensions by averaging values over a window. |
| Flatten | (None, 27) | 0 | Converts the 3D tensor into a 1D vector. |
| Dense | (None, 1800) | 28000 | Fully connected layer for final classification. |
| Total Parameters | | 3,08,323 | |
| Trainable Parameters | | 3,07,171 | |
| Non-trainable Parameters | | 1,152 | |

The loss metrics, illustrated in Figure 10, showcase a consistent downward trend, aligning with the anticipated behavior of the model during training. The optimal number of epochs that are considered for fine-tuning the training regimen strikes a balance between maximizing performance and preventing overtraining.

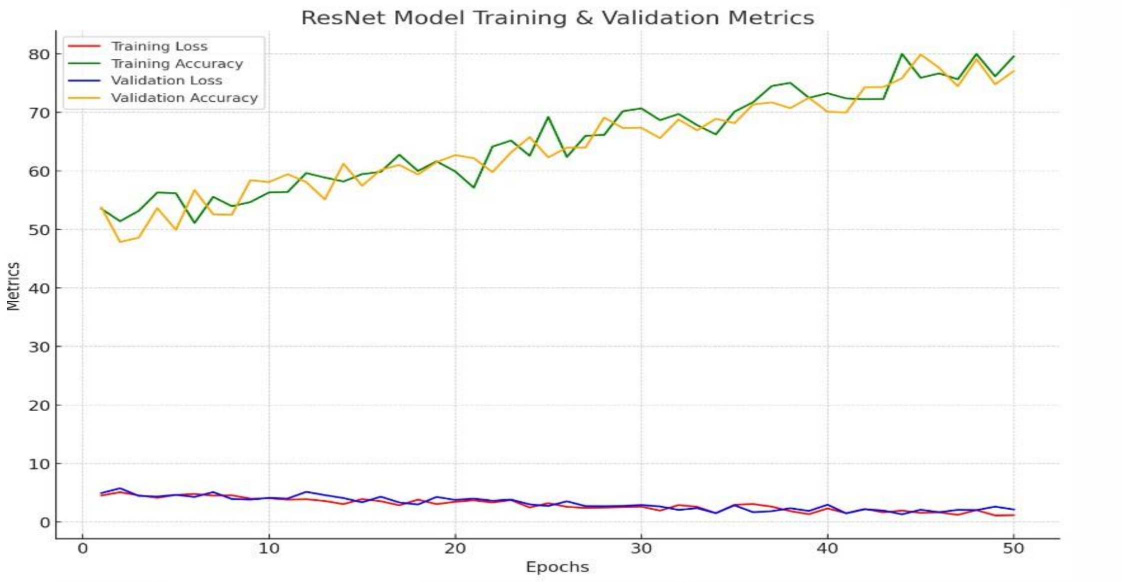



**Fig. 10.** Accuracy & Loss Performance of ResNet model

The loss metrics, illustrated in Figure 11, showcase a consistent downward trend, aligning with the anticipated behavior of the model during training.

We attribute the intermittent spikes in loss values to the model's essential resilience. As the training progresses, accuracy converges and loss decreases simultaneously. This shows that the model can effectively learn from the training dataset and apply what it has learned to the validation dataset. Figure 11 illustrates the convergence of accuracy and the corresponding reduction in loss, demonstrating the model's ability to effectively assimilate the training data and generalize it to validation data. We applied the proposed approach to a large-scale dataset, augmenting and diversifying it with GAN-generated samples to encompass various stages of breast cancer. This enhanced the representativeness of the training data by enabling the model to capture complex and simple patterns in breast cancer image representation more effectively. This consistent performance suggests that the model not only effectively learned similar features but also maintained high reliability across various image presentations.

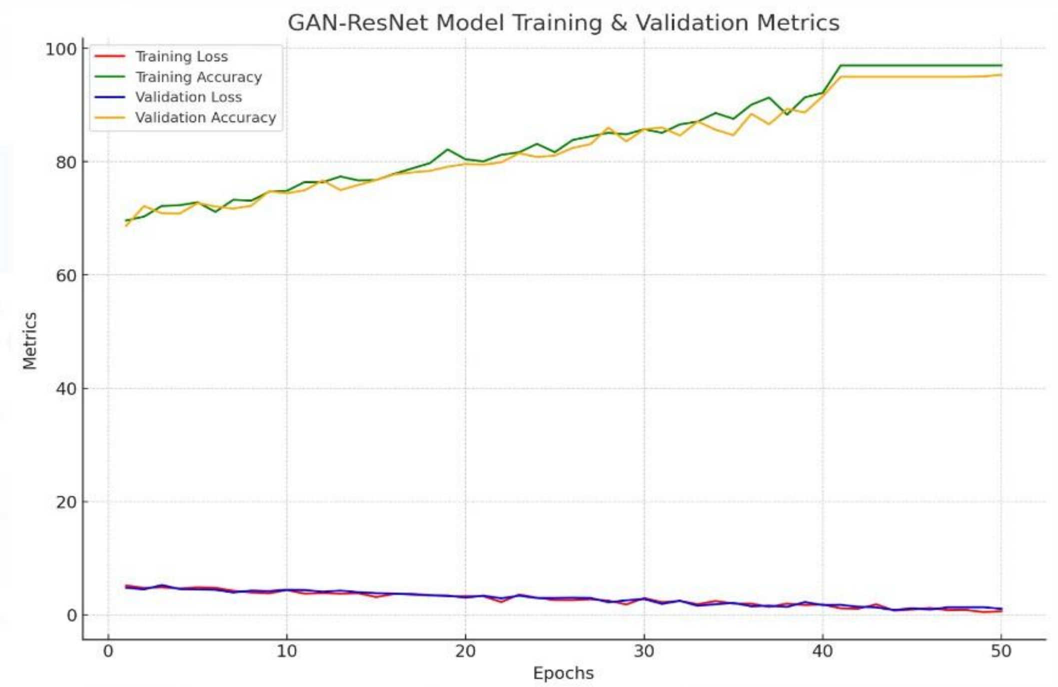



**Fig. 11.** Distribution of image based on breast density

**Table 2.** Proposed method results comparison with previous approaches

| Authors | Model used | Accuracy |
|---|---|---|
| Madallah Alruwaili et al. | ResNet | 70% |
| Dilovan Asaad Zebari et al. | CNN | 95. 71% |
| Proposed method | GAN+ResNet | 98% |

Table 2 shows that Madallah Alruwaili and colleagues' research, which used ResNet for breast cancer detection, only achieved an accuracy of 70%. Dilovan Asaad Zebari and their team employed a convolutional neural network (CNN) for breast cancer detection. Their model achieved a significantly higher accuracy of 95.71%. The proposed method, which combines GANs with ResNet, outperforms both previous approaches. Achieving an accuracy of 98%, this model demonstrates the potential of leveraging GANs for data augmentation and ResNet for classification. The fine-tuned binary classification layer ensures precise identification of malignant and benign breast tissue.

# 5 Conclusion

To perform effective breast cancer diagnosis, we have proposed a novel approach using a synergistic combination of generative adversarial networks (GANs) and residual neural networks (ResNet). Using GANs for data augmentation and ResNet for high-performance classification, the concept has demonstrated remarkable accuracy in analyzing histopathological images. The fine-tuned binary classification layer effectively distinguishes between malignant and benign tissue, enhancing early detection capabilities. Moreover, adjustments to the loss function address dataset imbalances, ensuring a robust and accurate model. Our findings validate the utility of this proposed model in efficiently detecting breast cancer at its early stage, potentially impacting patient outcomes and clinical practice.

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