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Early Detection of Breast Cancer Using Gan and Resnet Emulsion Approach

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Abstract: Breast cancer analysis is critical for clinical diagnosis and treatment. It is characterized by abnormal cell growth and tumor formation and remains a significant health concern among women. To address this issue, researchers have explored traditional and various individual deep learning algorithms, such as convolutional neural networks (CNNs) and artificial neural networks (ANNs). Furthermore, the mono-based model study could cause the model's classification accuracy to be low when using deep learning in medical diagnosis. So, to address this issue, we proposed a novel approach that combines generative adversarial networks (GANs) with residual neural networks (ResNet) for accurate breast cancer detection using histopathological images. The enriched dataset ensures better generalization during training, and we used GANs to supplement the training dataset. By generating synthetic images, GANs enhance feature recognition and improve model robustness. The augmented data fine-tunes ResNet, a powerful deep learning architecture, for classification. The GAN-ResNet channel uses discriminatory features extracted by the discriminator from GAN-generated images. This fusion combines GANs' discriminative power with ResNet's classification capabilities. We specifically fine-tuned the final model layer for binary classification, enabling it to distinguish between malignant and benign breast tissue. We adapt the loss function to handle imbalances in the medical dataset, ensuring a more robust and accurate model. Our proposed model demonstrates a remarkable 95% accuracy in analyzing histopathological images, validating its efficacy for early breast cancer detection at its earliest stage.

Keywords: *Breast cancer detection, Generative Adversarial Network (GAN), Residual Neural Networks, Convolutional Neural Networks, Machine Learning.*

1. Introduction

Breast cancer is a global health concern that affects millions of women worldwide. According to the World Health Organization (WHO), breast cancer caused 685,000 deaths globally in 2020. Breast is the most commonly diagnosed cancer type, accounting for 1 in 8 cancer diagnoses worldwide [1]. Breast cancer is a complex disease, and its exact cause is not known. However, certain factors increase the risk of developing breast cancer. Few of the reasons are lifestyle factors such as alcohol consumption, poor diet, physical inactivity, and obesity. Similarly, the genetic factors, family history of cancer for a person can inherently could also may impact etc. [2][3].

Tumor is described as an abnormal growth of a tissue which has no particular 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) tumors.

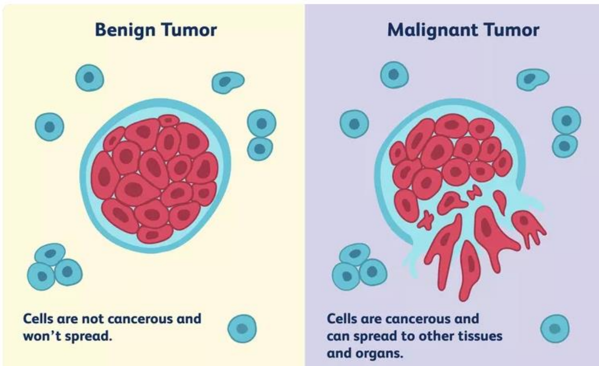

Fig. 1. Image of a Benign and Malignant tumor

Figure 1 explains the representation of benign and malignant tumors. Benign tumors don't harm any other tissues in the body and are different when compared with the surrounding cells. Malignant tumors these are made of cancer cells are abnormal and behave different from remaining or nearby tissues and grow without any control and invade nearby tissues. Malignant tumors which are cancerous can be present anywhere in the body. This paper dives into early detection of breast cancer and the classification is based on the specific cell types involved in the development of the disease. In terms of anatomy, the breast features glands that produce milk are situated anteriorly to the chest wall, resting upon the pectoralis major muscle and supporting ligaments connect the breast to the chest wall. The breast comprises 15 to 20 lobes arranged in a circular fashion. The size and shape of the breast are

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influenced by the fatty tissue enveloping the lobes. Within each lobe, lobules contain glands activated by hormonal stimuli for milk production. The development of breast cancer typically occurs without noticeable symptoms. People often become aware of the disease during routine screening procedures. Breast cancer stands as the prevalent cancer identified in women, representing over 10% of new cancer cases annually. Globally, it ranks as the second leading cause of cancer-related fatalities among women. Breast cancer risk factors encompass 7 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 [4][5] 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 Lump or Thickening which is often Painless, Sudden change in size, shape, or appearance of the breast, Skin Alteration, Nipple changes, Abnormal fluid from nipple

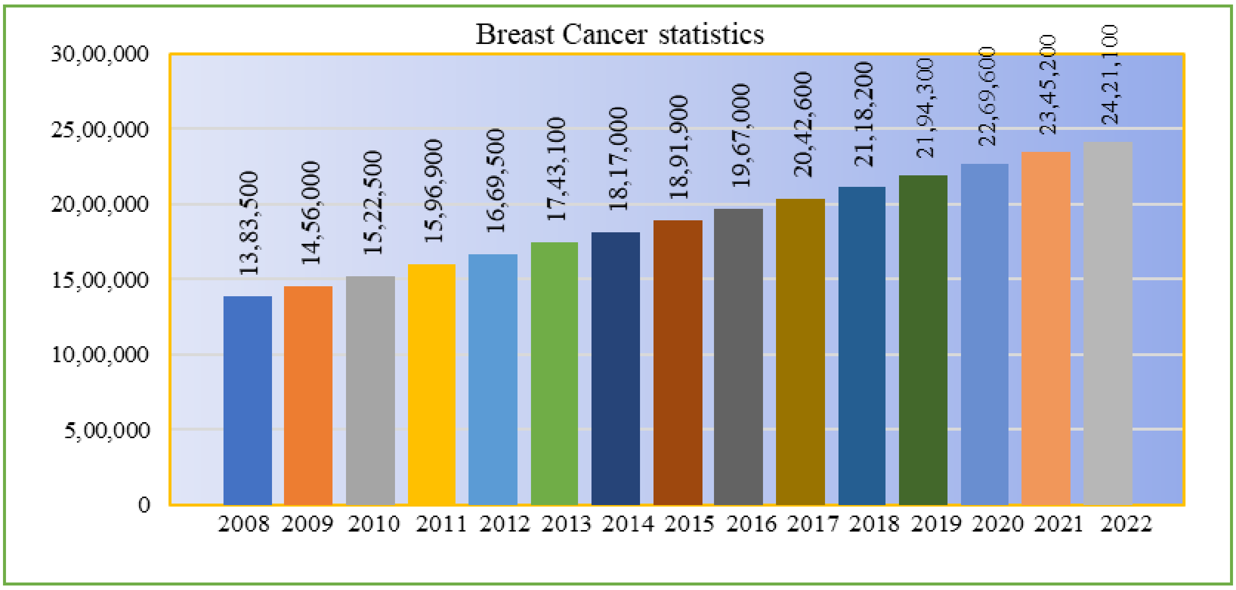

Fig. 2. 15-yearWHO breast cancer statistics (Source: [1])

As shown in above Figure indicates exponential growing of Breast cancer over the years which indicates there is a significant study requires for careful analysis and diagnosis. The early diagnosis of bosom cancer can improve the prognosis and the can increase the survival rate significantly. In addition, the accurate classification of benign tumors can prevent patients undergoing unnecessary treatments. Thus, the correct diagnosis of bosom cancer and classification cancer patients in terms of either malignant or benign group is the subject of much research. Deep learning methods are an effective way to classify data and has an advantage of critical features analysis over cancer data set. Especially in medical field, where those methods are widely used in diagnosis and analysis to make decisions. And also beneficial in identifying subtle indicators and early signs of diseases, providing healthcare professionals with valuable insights for improved and timely diagnosis by offering a more efficient and precise approach to disease detection and monitoring. Deep Learning techniques have been explored by other authors using histopathological images, offering valuable insights in the fields of pathology. Several approaches are such as Convolutional Neural Networks (CNN's) [6], Transfer Learning [7], Recurrent Neural Networks [8], Residual Network [9], and Generative Adversarial Networks etc. [10].

By harnessing the Collaborative Fusion Framework strengths of these three components, the Combined Force model aims to create a robust and accurate system for breast cancer detection. 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.

Detecting breast cancer from histopathological images is the central objective of this study. To achieve this, we investigate with GAN and ResNet models. The significance of this study would potentially contribute to efficient breast cancer detection and improving patient outcomes. To carryout our work effectively the following are the contributions required as follows.

- To perform the Feature Extraction Using GANs and Combine these extracted features with a ResNet architecture for breast cancer analysis.
- Hyperparameter tuning and contrasted data preprocessing techniques, with a focused examination of dataset undergoing adaptive equalization preprocessing and those without.

- Experimented with diverse optimizers during the model's training phase to discern the most efficient one.
- To evaluate the proposed methodology by using various metrics such as accuracy and loss performance scores.

The paper has been structured as follows. Section 2 presents the literature work about various works we have identified relevant to our work. Section 3 discusses our implemented framework, the algorithmic process we followed and the other techniques we had applied to accomplish our work. In Section 4 the obtained results have been illustrated. Conclusion and the references section presented subsequently.

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. [11] 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 incorporation of residual blocks addresses challenges such as gradient disappearance and model degradation often encountered in CNNs. This innovation enables the construction of exceptionally deep neural networks, facilitating more efficient training and optimization processes. In [12] a novel approach was introduced based on transfer learning to classify breast histology images into four distinct histological 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. Specifically, the ResNet50 network was employed for conducting test classifications in this proposed method. [13] A framework was designed for the automatic detection of breast cancer, leveraging 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 [14] an innovative approach was proposed for detecting breast cancer in mammography images, employing CNN-based transfer learning, specifically within the realm of DL methods. This model demonstrated an impressive accuracy of 95.71% on the mini-dataset, surpassing the performance of other existing methods. Addressing the common challenge of class imbalance in breast cancer image classification, where malignant samples are typically limited compared to benign samples, it was highlighted that the potential bias introduced during training. To mitigate this, an attention mechanism was incorporated in their method, 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. [15] 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. This approach aims to leverage the capabilities of GANs for generating synthetic images that mimic both cancerous and non-cancerous scenarios, thereby enhancing the diversity and richness of the dataset for more robust model training and evaluation. CNNs are equipped with at least one Convolution layer, where the conventional matrix multiplication is replaced by a convolution operation applied to the input matrix. This specialized operation is employed to extract discernible low-level and high-level features from the image, facilitating the network in learning and representing intricate patterns inherent in the visual data [16]. CNNs have the capacity to acquire a greater number of features by expanding the depth of the network. Nevertheless, augmenting the depth of the network introduces challenges such as vanishing gradients and degradation [17].

These issues can impede the effective training and optimization of the network, limiting its ability to learn and generalize well on complex tasks. Techniques like skip connections and residual learning have been introduced to mitigate these problems and enable the successful training of deeper networks. A framework led to a more straightforward optimization of the network, resulting in higher accuracy [18]. 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 [19], 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 approach emphasizes the importance of leveraging features derived from nuclei to enhance the accuracy and effectiveness of cell classification in medical applications, particularly in distinguishing between benign and malignant cells. Likewise, clustering-based algorithms, in combination with the circular Hough Transform and diverse statistical features, are harnessed for nuclei segmentation and classification [20-22].

In the realm of medical image analysis, algorithms designed for histopathological images are advancing rapidly. However [23-25] 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, particularly DNNs have demonstrated significant success in automatically learning hierarchical representations from complex data, offering improved capabilities in tasks such as image classification and feature extraction [26, 27]. CNN has achieved success in the field of biomedical image analysis like detection of mitosis cells from microscopic images, tumor detection, segmentation of neural membranes, classification of skin disease, detection and classification of cells immune and mass of mammograms [28-34]. Multiple CNN architectures boost up the performance of learning and replace the use of traditional single model CNN architecture. Similarly, the combination of ResNet50, InceptionV2 and InceptionV3 are pre-trained on ImageNet to produce a fast and accurate model for cell-based image classification and are pre-trained on ImageNet which produced a fast and accurate model [35, 36].

Most of the above mentioned works they didn't focus much on using fusion based approach mostly focused on employing mono based model implementation. The Combined GAN and ResNet would helps us to get better beneficiary informed results. The experimentation how we have carried and its results has been in a detailed manner in the next forthcoming sections methodology and 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. Figure 3 shows the proposed system architecture workflow framework of breast cancer detection using Generative Adversarial.

Networks (GANs) involves the below steps:

Data Collection: With the large dataset of breast images, including both normal and cancerous tissues the images should be labelled to indicate whether they contain cancerous cells or not.

Data Preprocessing: The images are pre-processed into standard terms of size, resolution, and colour. 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 Generator generates realistic breast images, while the discriminator exemplifies the difference between real and generated images.

Feature Extraction: From the generated images relevant features are extracted using the generator network. These features capture important characteristics of breast tissues that can aid in cancer detection.

Classifier Training: A convolutional neural network-based classifier (ResNet) is applied on the extracted features to classify images as either normal or cancerous. Performance of the trained classifier is evaluated using a separate test dataset. Measures such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve are used to assess the model's effectiveness in detecting breast cancer.

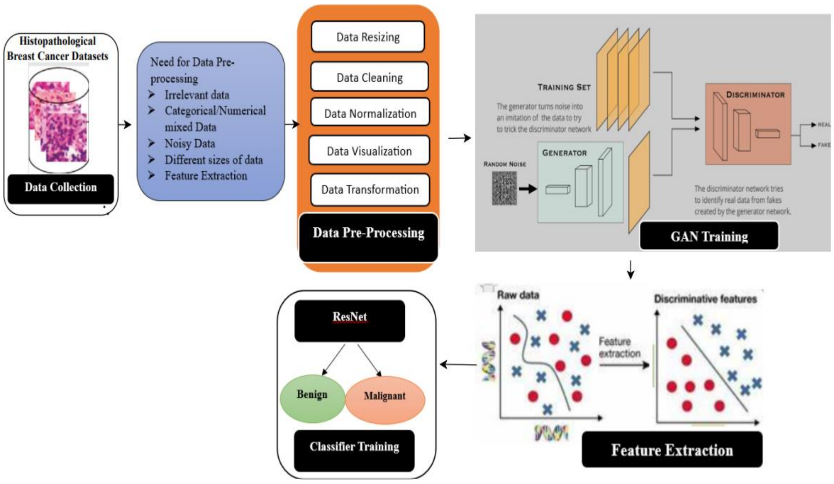

Fig. 3. Proposed System Architecture

The model's performance is validated on additional datasets and the parameters are changed accordingly if necessary to improve performance and generalization.

Deployment: The trained model is deployed such that it analyses new breast images and provide predictions regarding the presence of cancerous cells, assisting healthcare professionals in making accurate diagnoses.

The performance of Augmentation Techniques while preprocessing the data; 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. Additionally, augmenting image data can be utilized to enhance the model's effectiveness and diminish 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 necessitated 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. The model requires input images to conform to a 224×224 shape, which is accomplished through training augmentation techniques.

The acquired data originates from various origins, yet it is unorganized and requires tidying and preprocessing prior to analysis. This 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. Noise within a dataset can be mitigated through techniques such as smoothing and aggregation. Integration of data from diverse origins is essential in crafting a comprehensive data analysis narrative, wherein the significance of results is contingent upon the quantity and quality of the data. Optimal outcomes are attained when both data quality and quantity are high.

The pre-processed dataset which uses GAN framework has a generator and a discriminator, the GAN methodology follows an iterative approach, by alternating updates to the discriminator and generator. The optimization process is steered by specific loss functions: binary cross-entropy for the discriminator, seeking to maximize the log-likelihood of accurate labels, and a generator loss inversely correlated with the discriminator's certainty regarding synthetic images.

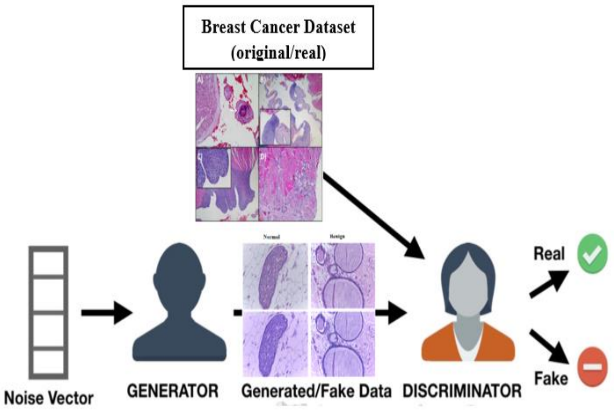

Fig. 4. The Generator and Discriminator of GAN applied on preprocessed data

In this research, the GAN workflow consists of two primary components as shown in the Figure 4: the generator, responsible for generating similar images, and the discriminator, tasked with scrutinizing them. Not only pivotal for evaluating the generator's output, the discriminator also functions as a potent 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. Leveraging ResNet robust feature representation, enhanced by skip connections combating gradient vanishing, further improves breast cancer classification beyond the discriminator's capabilities in the GAN technique.

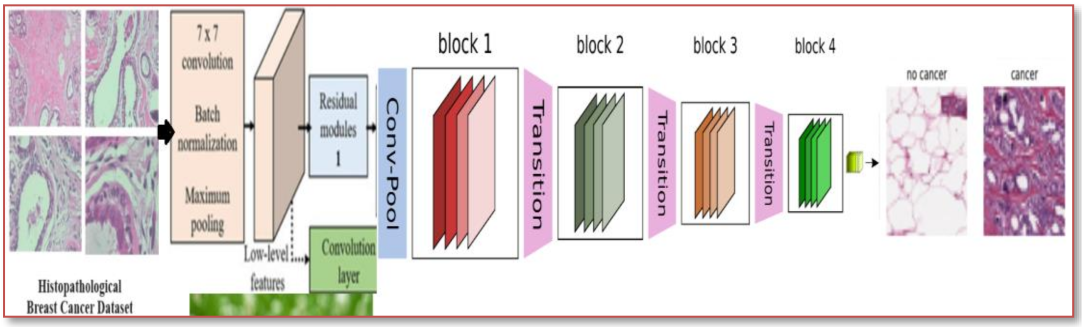

Fig. 5. Feature Extraction using RESNET

Figure 5, explains the extraction of features using ResNet, short for Residual Network, employs a 34-layer basic network structure inspired by VGG-19 from the Visual Geometry Group. This architecture incorporates shortcut connections, transforming it into a residual network. It adheres to two fundamental design principles: maintaining the same number of filters across layers for consistent output feature map sizes, and doubling the number of filters when the feature map size is halved to uphold time complexity per layer. With 34 weighted layers, shortcut connections are integrated into the basic network. When input and output dimensions coincide, identity shortcuts are directly applied. For increased dimensions, two approaches are considered: either the shortcut continues with identity mapping while padding extra zero entries, or a projection shortcut is utilized to align dimensions.

In the proposed methodology as shown in figure 6, the ResNet architecture is pre-trained on an extensive image dataset, undergoes fine-tuning with feature extraction from fundus images, tailoring its comprehensive feature extraction power specifically for ophthalmologic images. This fine-tuning process enables ResNet to adapt its pre-learned filters to the unique features present in these images. By integrating the ResNet model into the GAN's feature extraction phase, we establish a pipeline that initially utilizes the GAN to augment data and highlight salient features. Subsequently, ResNet is employed for high-precision classification, ensuring that the classification benefits from both the GAN's ability to synthesize and enhance glaucoma-specific features and ResNet's proficiency in deep feature learning and abstraction. This integrated GAN-ResNet workflow showcases the ResNet's convolutional layers further abstracting the GAN's feature extraction, thereby ensuring that the identification process isn't solely reliant on raw pixel data but also includes representations of retinal features. Such abstraction proves crucial in identifying subtle patterns distinguishing between malignant and benign histopathological images. The ResNet's deeper layers, coupled with its residual connections, enable the training of complex patterns without the risk of overfitting, mitigating concerns commonly associated with deep neural networks.

In the final stages, the classification layer of ResNet is customized for the binary classification task of distinguishing between glaucoma and normal healthy images. During the learning phase, the model's weights are optimized using a loss function that accounts for the unequal distribution of classes

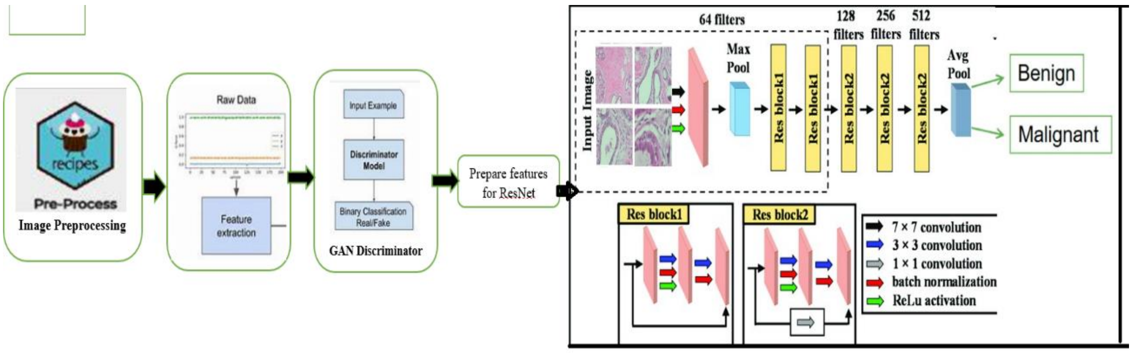

Fig. 6. GAN-ResNet Feature Integration Pipeline

within medical datasets, ensuring sensitivity to clinically significant but less prevalent cases, such as breast cancer images. Extensive experimentation and validation on a large dataset demonstrate the integrated GAN-ResNet model's exceptional performance in breast cancer classification. 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

In this study, we explored a novel deep learning architecture that leverages the generative capabilities of Generative

Adversarial Networks (GANs) integrated with ResNet for the early identification of breast cancer from histopathological images. The developed model underwent comprehensive evaluation and comparison with traditional convolutional neural network architectures such as standalone GAN and ResNet-50. The proposed approach was applied to a large-scale dataset, augmented and diversified using GAN-generated samples to encompass various stages of breast cancer, thereby enhancing the representativeness of the training data.

Following data augmentation, ResNet was fine-tuned on this expanded dataset, enabling the model to capture complex and simple patterns in breast cancer image representation more effectively. Furthermore, the proposed model demonstrated admirable consistency in evaluation, with testing accuracy ranging from 95.00% 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 targeted achieving high mean accuracy but 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 there by displaying Count Plot on Dataset regarding images with cancer as 1 and without cancer as 0 as shown in Figure 7.

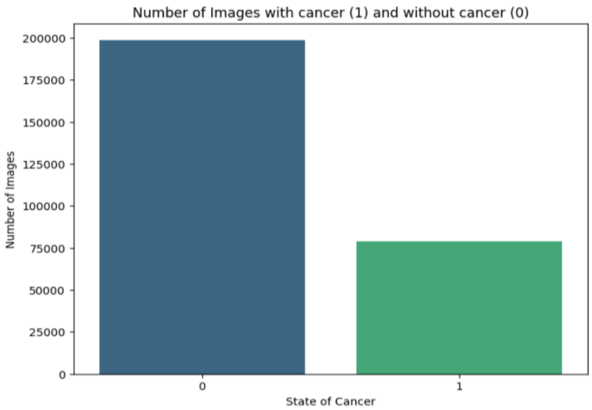

Fig. 7. Displaying Count Plot on Dataset regarding images with cancer as 1 and without cancer as 0

Number of Images of no cancer: 198738

Number of Images of cancer: 78786

Total Number of Images: 277524

Figure 8 explains images are distributed based on pathology and the image count is evaluated in the order of image properties like spatial coverage, size, colour and texture.

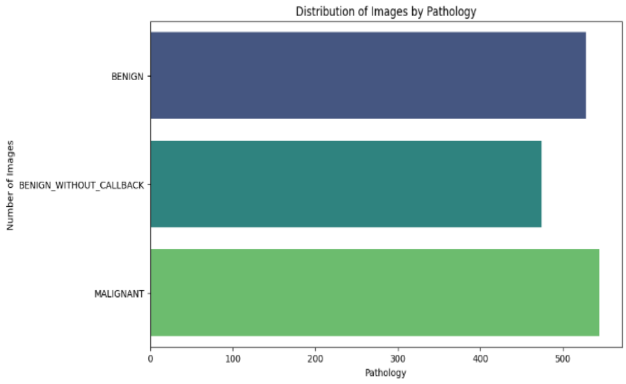

Fig. 8. Count on distribution of image properties

As part of visualizing and data cleaning the images are sorted by GAN based on specific attribute like breast density. A dataset containing histopathological images of breast tissue is collected. These images may vary in terms of breast density, which is an important attribute in breast cancer diagnosis. The GAN is then employed to sort these images based on their breast density attribute.

After sorting, the dataset is visualized to understand the distribution of images across different breast density categories. Visualization techniques such as scatter plots, histograms, or heatmaps can be utilized to provide insights into the distribution and density of images in each category. Distribution of images based on breast density using histogram visualization is shown in Figure 9.

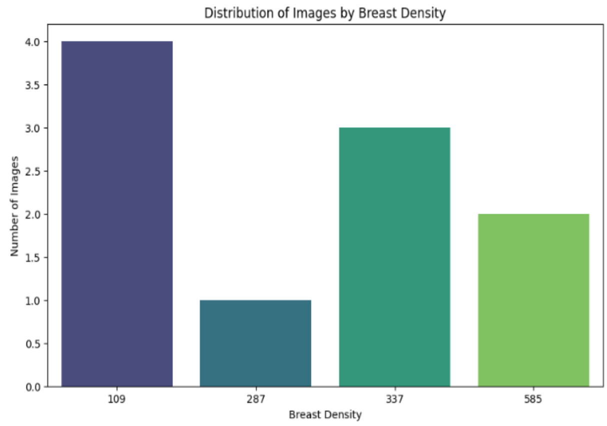

Fig. 9. Distribution of image based on breast density

Figure 10, explains analyzing the results of displaying the ResNet model summary at different layers into its hierarchical feature extraction process. The hyperparameters considered for implemented Neural network model are such as Activation layer, Optimizer, Learning rate, Batch size, Epochs, Normalization, and Dropout rate. This examination showcases how the model progressively refines and abstracts information throughout 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-tune the training regimen, striking a balance between maximizing performance and preventing overtraining. The loss metrics, illustrated in Figure 11, showcase a consistent downward trend, aligning with the anticipated behavior of the model during training.

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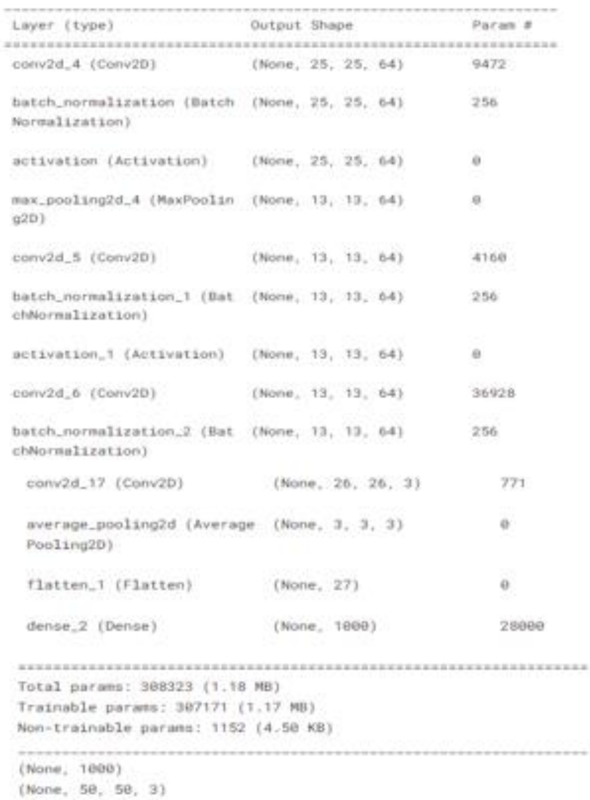

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (Conv2D)            (None, 25, 25, 64)        9472

batch_normalization (Batch   (None, 25, 25, 64)        256
Normalization)

activation (Activation)      (None, 25, 25, 64)        0

max_pooling2d_4 (MaxPoolin   (None, 13, 13, 64)        0
g2D)

conv2d_5 (Conv2D)            (None, 13, 13, 64)        4160

batch_normalization_1 (Bat   (None, 13, 13, 64)        256
chNormalization)

activation_1 (Activation)    (None, 13, 13, 64)        0

conv2d_6 (Conv2D)            (None, 13, 13, 64)        36928

batch_normalization_2 (Bat   (None, 13, 13, 64)        256
chNormalization)
  conv2d_17 (Conv2D)           (None, 26, 26, 3)         771

  average_pooling2d (Average   (None, 3, 3, 3)           0
  Pooling2D)

  flatten_1 (Flatten)          (None, 27)                0

  dense_2 (Dense)              (None, 1000)              28000

=================================================================
Total params: 308323 (1.18 MB)
Trainable params: 307171 (1.17 MB)
Non-trainable params: 1152 (4.50 KB)
_________________________________________________________________
(None, 1000)
(None, 50, 50, 3)
```

Fig. 10. Displaying ResNet model summary at different layers

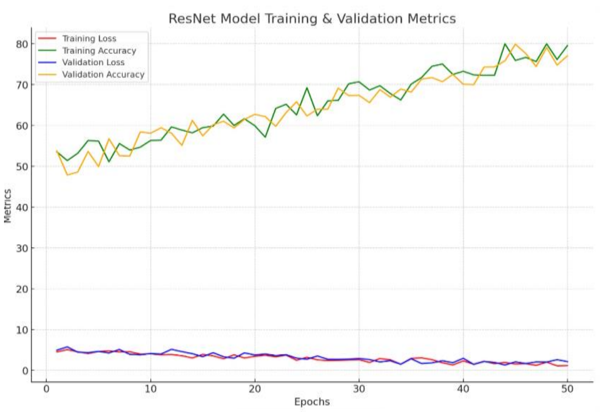

Fig. 11. Accuracy & Loss Performance of ResNet model

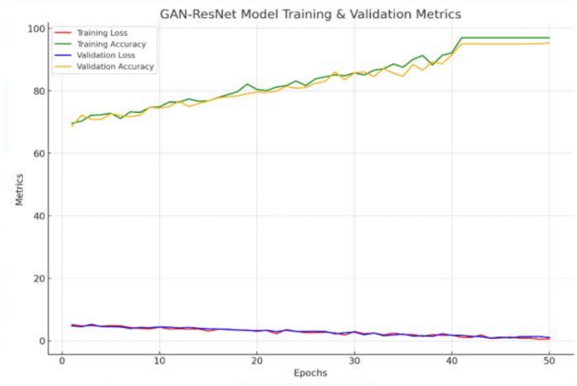

Fig. 12. Accuracy & Loss Performance after combing GAN & ResNet model

The intermittent spikes in loss values are attributed in fostering essential resilience within the model. As the training unfolds, a convergence of accuracy and a simultaneous decline in loss become evident, signifying the model's adeptness in assimilating the training dataset and extending its knowledge to validation data with efficacy. The figure 12 represents convergence of accuracy and a corresponding reduction in loss are observed, indicating the model's capacity to assimilate the training data and generalize to validation data effectively. The proposed approach was applied to a large-scale dataset, augmented and diversified using GAN-generated samples to encompass various stages of breast cancer, thereby enhancing 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.

Table 1: 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%

Based on the Table on 1 it can be seen that the research conducted by Madallah Alruwaili and colleagues utilized ResNet for breast cancer detection and obtained an accuracy of 70% only. 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). By leveraging GANs for data augmentation and ResNet for high-performance classification. The concept has achieved a 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.

6. Declarations

Ethics approval and consent to participate

This manuscript does not contain any studies with human participants or animals performed by the author.

Availability of data and materials

Upon a reasonable request, the sources and other pertinent information will be provided.

Competing interest

The authors certify that they have no financial or other competing interests to disclose with regard to the current work.

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Author's contributions

The first author carried out the methodology, data curation, experiments, and draft preparation. In addition to providing supervision, the co-author also helped with conceptualization, validation, review, and editing.

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