SRM INSTITUTE OF SCIENCE AND TECHNOLOGY
SCHOOL OF COMPUTING
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Artificial Intelligence Of Things - 21CSE292P

Breast Cancer Using DCGAN

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Abstract

- Current machine learning methods for breast cancer classification face limitations in effectiveness.
- Our proposed approach advocates for the integration of generative artificial intelligence to enhance diagnostic capabilities.
- We propose the utilization of a Deep Convolutional Generative Adversarial Network (DCGAN) to generate authentic synthetic images of breast tissue, including both healthy and cancerous samples.
- CNN and Transfer learning techniques will be employed to optimize a classification model for distinguishing between benign and malignant tissue types.
- Image augmentation methods will be applied to increase dataset size and diversity, thereby improving the robustness of the model.
- This initiative aims to significantly enhance the accuracy and accessibility of breast cancer diagnosis, potentially revolutionizing medical practice and patient care.

Introduction

- Breast cancer poses a significant threat to women's health globally, necessitating early detection for successful treatment.
- Current machine learning methods for breast cancer classification have limitations.
- This project suggests a new approach utilizing generative AI to enhance breast cancer diagnosis.
- The proposed method involves developing a DCGAN model to produce realistic synthetic images of breast tissue, encompassing both benign and malignant cases.
- Transfer learning will be employed to optimize the classification model's performance.
- The project aims to evaluate the effectiveness of synthetic images generated by the DCGAN in distinguishing between benign and malignant breast tissue.
- If successful, this project could enhance the accuracy and accessibility of breast cancer diagnosis.

Motivation

- Data Imbalance: Real-world medical datasets may be imbalanced, with a higher proportion of benign cases compared to malignant ones. This can hinder the model's ability to accurately identify cancer.
- Limited Accuracy: Current machine learning methods for breast cancer classification may not achieve optimal accuracy, potentially leading to missed diagnoses or unnecessary biopsies.
- Data Scarcity: Training effective machine learning models often requires vast amounts of real medical data, which can be limited due to privacy concerns or data collection challenges.
- Accessibility Issues: Certain diagnostic procedures used in breast cancer detection can be expensive, invasive, or have limited availability in some regions.
- By leveraging generative AI, this project aims to address these limitations and contribute to a more effective and accessible approach to breast cancer diagnosis.

Literature Review

S.no	Title & Published year	Author	Description	Limitations
1	Prior-Guided Generative Adversarial Network for Mammogram Synthesis (2023)	Annie, Julie Joseph, Priyansh Dwivedi, Jiffy Joseph, Seenia Francis, Pournami P.N., and Jayaraj P.B.	This research employs a conditional generative adversarial network (cGAN) to address the issue of class imbalance in mammogram datasets. Traditional medical image datasets often suffer from class imbalance, meaning there are significantly more images of one type (e.g., normal tissue) compared to others (e.g., malignant masses). This makes training machine learning models for tasks like cancer detection less effective. The researchers utilize an existing mammogram dataset, likely containing mostly normal images. They design and train a cGAN with two components: Generator, Discriminator. The researchers assess the quality of the generated images using metrics like FID (Fréchet Inception Distance) and compare them to real mammograms. Additionally, they train machine learning models on both the original and balanced datasets and compare their performance in classifying mammograms, particularly focusing on identifying malignant cases.	• Generative Adversarial Networks (GANs) necessitate a substantial quantity of high-quality training data to effectively learn the underlying distribution and produce realistic samples. • GANs are susceptible to mode collapse, a phenomenon where they may inadequately capture the full diversity of the training data, resulting in the generation of limited variations. • The effectiveness of the proposed conditional GAN (cGAN) model could fluctuate when applied to disparate datasets with unique characteristics. Therefore, additional validation and testing on diverse datasets are imperative to accurately evaluate its generalization capabilities.
2	Synthesis of Mammogram From Digital Breast Tomosynthesis Using Deep Convolutional Neural Network With Gradient Guided cGANs (2021)	Gongfa Jiang, Jun Wei, Yuesheng Xu, Zilong He, Hui Zeng, Jiefang Wu, Genggeng Qin, Weiguo Chen, Yao Lu	The paper presents a novel approach to enhance the quality of synthesized digital breast tomosynthesis mammography (SDM) images, derived from corresponding digital breast tomosynthesis (DBT) volumes. Leveraging intricate objective functions and a pre-trained VGG-16 neural network for feature extraction, the research endeavors to enhance the perceptual quality of SDM images. Training procedures involve meticulous data preprocessing, encompassing rescaling and patch extraction, alongside the utilization of diverse objective functions during the training phase. Through a series of experiments, the study assesses the efficacy of different objective functions in terms of intensity distortion, mass segmentation, MC sharpness, and human observer studies. Encouragingly, the results demonstrate notable enhancements in image quality metrics, particularly in preserving mass edges and MCs, with the proposed method exhibiting superior performance	• The study lacks a reader detection study, which could provide valuable insights into the performance of the proposed method from a reader's perspective. • The limited reporting of only two cases in the MC detection experiment is attributed to the time-consuming nature of annotation, highlighting a potential limitation in the scope of the study. • Absence of statistical comparisons with C-view/Intelligent 2D due to regulatory constraints may limit the comprehensive evaluation of the proposed method against existing standards. • Failure to evaluate MC detection as a

S.no	Title & Published year	Author	Description	Limitations
4	**Reliable Breast Cancer Diagnosis with Deep Learning: DCGAN-Driven Mammogram Synthesis and Validity Assessment 2024**	**Dilawar Shah, Mohammad Asmat Ullah Khan, Mohammad Abrar**	**The project proposes utilizing DCGANs to generate synthetic mammograms for breast cancer detection.It covers data collection from DDSM, denoising, and resizing. Detailed DCGAN architecture for mammogram generation is presented, along with training processes and loss functions. Data Preparation:A denoising algorithm, such as median filtering or wavelet denoising, is applied to the mammogram images to reduce noise and ensure consistency .** **Generator Network:A random noise vector is fed into the generator network, which gradually converts it into synthetic mammogram images.It starts with convolutional layers and then adds nonlinearity with batch normalization and ReLU activation functions. Skip connections preserve key features during the downsampling process; they were inspired by U-Net architectures.** **The primary function of the discriminator network is to discern and differentiate between authentic mammogram images and artificially generated ones.** **Loss Function: Employing binary cross-entropy and Wasserstein loss functions during training.**	◦ **Reliance on the DDSM dataset limits generalizability to other datasets with different characteristics.** ◦ **The dataset's focus on specific mammogram abnormalities may not capture the full spectrum of breast cancer cases.** ◦ **The paper lacks exploration of additional datasets and diverse GAN architectures, indicating a gap in comprehensive testing and evaluation.** ◦ **the evaluation metrics may not fully capture the clinical relevance of synthetic mammograms.**
5	**Improving Cancer Detection Classification Performance Using GANs in Breast Cancer Data 2023**	**EMILIJA STRELCENIA AND SIMANT PRAKOONWIT**	**Introduces various GAN architectures such as Wasserstein GAN (WGAN), Non-Saturating GAN (NS-GAN), Least Square GAN (LS-GAN), and Synthetic Data Generation GAN (SDG GAN). like GAN value function and emphasizes the training process, highlighting the minimax game between the Generator and Discriminator networks. WGAN utilization of Earth Mover distance to enhance training stability and mitigate mode collapse issues.NS-GAN's modification of the Generator loss to tackle saturation problems and enhance training stability.LS-GAN, which incorporates least square loss functions for the Discriminator to address challenges such as vanishing gradients during training. SDG GAN's role in generating synthetic data for training supervised classifiers, including its feature matching loss and conditional GAN structure.** **the Novelty K-CGAN model, its Generator and Discriminator sub-networks along with their respective training procedures.** **Novel Loss Function for K-CGAN: it combines binary cross-entropy and KL divergence to effectively train the Generator and Discriminator networks.** **Adversarial Training Framework for K-CGAN: This part explains the adversarial training framework for K-CGAN, emphasizing the roles of binary cross-entropy and KL divergence terms in the Generator loss.** **Training Procedure Overview: Finally, a brief overview of the steps involved in training the K-CGAN model, including dataset preparation and model optimization.**	**They used the WDBC dataset, which consists of data from 569 patients. While this dataset is widely used for breast cancer research, it may not fully represent the diversity and complexity of real-world clinical data. The study relies on synthetic data generated by the K-CGAN model to address the issue of limited training data. While synthetic data generation can be a useful approach, there may be limitations in how well the generated data reflects the underlying distribution of real patient data. The effectiveness of the K-CGAN method in generating realistic and clinically relevant synthetic data should be further validated.**

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5	Deep transfer with minority data augmentation for imbalanced breast cancer dataset 2020	Manisha Saini, Seba Susan	This paper introduces an innovative deep learning methodology for breast cancer classification utilizing histopathological images sourced from the BreakHis dataset. The method tackles the challenge of imbalanced data, where benign (non-cancerous) tissue images significantly outnumber malignant (cancerous) tissue images. The approach leverages a pre-trained VGG16 network for feature extraction, supplemented by additional layers tailored for breast cancer classification. Furthermore, it employs DCGAN for data augmentation, generating synthetic images of the minority class (benign) to rebalance the dataset. Remarkably, the proposed methodology achieves high accuracy in classifying both benign and malignant samples across different magnification factors (40X, 100X, 200X, 400X). Comparative analysis against state-of-the-art networks demonstrates superior performance attributed to the balanced dataset and efficient feature extraction techniques employed.	◦ DCGAN's performance is sensitive to the number of minority class samples, potentially leading to subpar results with very few samples. ◦ Further validation across larger datasets and diverse medical applications is necessary. ◦ While effective for addressing class imbalance, the method may be less suitable for extreme cases of severe imbalance. ◦ Limited exploration of pre-trained networks and GAN variants like VGG16 and DCGAN necessitates further investigation.
6	Breast Cancer Detection Using GAN for Limited Labeled Dataset 2020	Shrinivas D Desai; Shantala Giraddi; Nitin Verma; Puneet Gupta; Sharan Ramya	This paper tackles the challenge of limited labeled data in breast cancer classification using mammograms. The authors introduce a Deep Convolutional Generative Adversarial Network (DCGAN) to produce realistic synthetic mammograms, aiming to augment the original dataset and potentially enhance classification accuracy. DCGAN effectively generates synthetic mammograms closely resembling the original images. By integrating these synthetic images with the original dataset, classification accuracy improves significantly (87% vs. 78.23%) compared to using only the original data. Image analysis confirms the similarity between original and synthetic images, with some synthetic images successfully deceiving expert physicians.	◦ Limited Dataset Size: The study's dataset comprises only 287 mammographic images (74 cancerous, 213 normal), potentially limiting the model's generalizability. ◦ Sole Validation on DDSM Dataset: Solely validating on the DDSM dataset may limit evidence for the model's effectiveness. Validation on multiple datasets is crucial for comprehensive assessment. ◦ Lack of Hyperparameter Exploration: The study doesn't explore crucial hyperparameters like learning rates or batch sizes, which could significantly improve the model's performance

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7	Breast cancer detection using synthetic mammograms from generative adversarial networks in convolutional neural networks 2019	Shuyue Guan and Murray Loew	The paper describes a method for image augmentation using Generative Adversarial Networks (GANs) to improve the performance of Convolutional Neural Network (CNN) classifiers in detecting breast cancer from mammographic images. Image augmentation is proposed as a solution to Training CNNs from scratch requires a large amount of labeled data , where synthetic images are generated to supplement the training dataset. Two methods of image augmentation are explored: Affine Transformation and GANs. Affine transformations involve applying random geometric modifications such as rotation, scaling, and flipping to original images. Different padding methods are used to maintain the image size and shape after transformation.. GANs consist of two neural networks, a generator and a discriminator, which are trained simultaneously in a competitive manner. The generator generates synthetic images, while the discriminator tries to distinguish between real and synthetic images. The goal is to train the generator to produce synthetic images that are indistinguishable from real ones.The GAN is trained using a limited number of real samples. The generator takes random noise vectors as input and generates synthetic images, which are then fed into the discriminator along with real images. The discriminator learns to distinguish between real and synthetic images, while the generator learns to produce more realistic images to fool the discriminator.	◦ the ability of the current GAN architecture (DCGAN) to produce realistic images without artifacts, will affect the the performance of classifiers trained on them. ◦ The performance of the GAN did not meet theoretical expectations, as the distributions of the synthetic images differed from those of real images. ◦ simply augmenting the dataset with synthetic images may not be sufficient to improve classifier performance. ◦ The study primarily focused on classifying abnormal and normal ROIs, without considering benign and malignant tumors.
8	ULTRASOUND IMAGE SYNTHETIC GENERATING USING DEEP CONVOLUTIO N GENERATIVE ADVERSARIAL NETWORK FOR BREAST CANCER IDENTIFICATI ON	Dina Zatusiva Haq | Chastine Fatichah	The paper discusses the development of a breast cancer identification system based on breast ultrasound image classification using two main methodologies: Deep Convolution Generative Adversarial Networks (DCGAN) and GoogleNet. Deep learning methods, such as CNNs, are effective for image analysis, with CNNs like GoogleNet performing well in medical image classification. they have used The dataset consists of breast ultrasound images divided into three classes: normal, benign, and malignant. K-fold cross-validation is used to divide the dataset into training and testing sets. Deep Convolution Generative Adversarial Networks (DCGAN): DCGAN is employed to handle imbalanced data problems by generating synthetic images to augment the dataset. GoogleNet: GoogleNet, a CNN architecture, is utilized for image classification. It includes inception modules to reduce parameters without sacrificing performance. Evaluation System: The performance of the classification system is evaluated using metrics like accuracy, sensitivity, and specificity, calculated from the confusion matrix.	◦ The quality of synthetic images generated by the DCGAN method is crucial for the effectiveness of data augmentation. the subjective assessment of image quality not fully reflect how well the synthetic images capture relevant features for classification. ◦ dataset not fully capture the diversity of breast ultrasound images encountered in real-world clinical settings. A larger and more diverse dataset could improve the generalizability of the model.

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S.no	Title & Published year	Author	Description	Limitations
9	DCGANs for Realistic Breast Mass Augmentation in X-ray Mammography 2019	Basel Alyafi , Oliver Diaz, Robert Marti	The study utilizes the OPTIMAM Mammography Image Database (OMI-DB), which contains digital mammograms from the NHS Breast Screening Programme of the United Kingdom. DCGANs are employed to generate realistic breast masses. DCGANs consist of two neural networks: a generator (G) and a discriminator (D). The generator learns to map a random noise vector from a latent space to realistic breast mass images, while the discriminator learns to distinguish between real and synthetic images. The DCGAN is trained using real breast mass images to learn the distribution of the input data. The synthetic breast mass images generated by the DCGAN are used to augment the original dataset. conventional data augmentation techniques such as horizontal and vertical flipping are applied to increase the diversity of the generated images.A fully-convolutional network classifier is trained on the augmented dataset to classify breast masses. The classifier architecture is similar to the discriminator of the DCGAN. The performance of the classifier is evaluated using the F1 score metric on a 1:10 imbalanced dataset of mass lesions and normal tissue patches.	◦ DCGANs can generate realistic breast mass patches, there may still be limitations in the quality and diversity of the synthetic images produced. the challenge of imbalanced datasets by generating synthetic minority class samples, there may still be limitations in the representation of rare or unusual cases. The synthetic images generated by DCGANs may not fully capture the variability and complexity of real breast masses, leading to potential biases in the classifier's performance.
10	Using Generative Adversarial Networks and Transfer Learning for Breast Cancer Detection by Convolutional Neural Networks 2019	Shuyue Guan , Murray Loew	the paper involves using a combination of Generative Adversarial Networks (GANs) and Transfer Learning (TL) with Convolutional Neural Networks (CNNs) for the detection of abnormalities in mammograms. The study collected a dataset of original (real) abnormal and normal Regions of Interest (ROIs) from mammograms. They augmented this dataset using GANs to generate synthetic abnormal and normal ROIs to increase the diversity of training data.The authors conducted experiments using different combinations of original and synthetic ROIs for training and validation. They trained CNN classifiers both from scratch and using TL with a pre-trained VGG-16 model The CNN architecture consists of convolutional layers adapted from the pre-trained VGG-16 model, followed by a fully connected layer with ReLU activation and dropout, and a sigmoid output layer for binary classification.TL involves using the pre-trained VGG-16 model to extract features from mammographic images, with only the weights in the fully connected layer being trained from scratch.	There may be discrepancies between synthetic and real images, potentially impacting the performance of the CNN classifiers. More complex architectures with multiple fully connected layers or additional convolutional layers might yield better performance in detecting abnormalities in mammograms. The study does not provide detailed analysis or visualization of the learned features by the CNNs. Understanding the specific features learned from mammographic images could offer insights into performance and areas for improvement. The study focuses on binary classification of abnormal versus normal ROIs and does not explore more nuanced classification tasks, such as distinguishing between different types of abnormalities or classifying the severity of abnormalities.

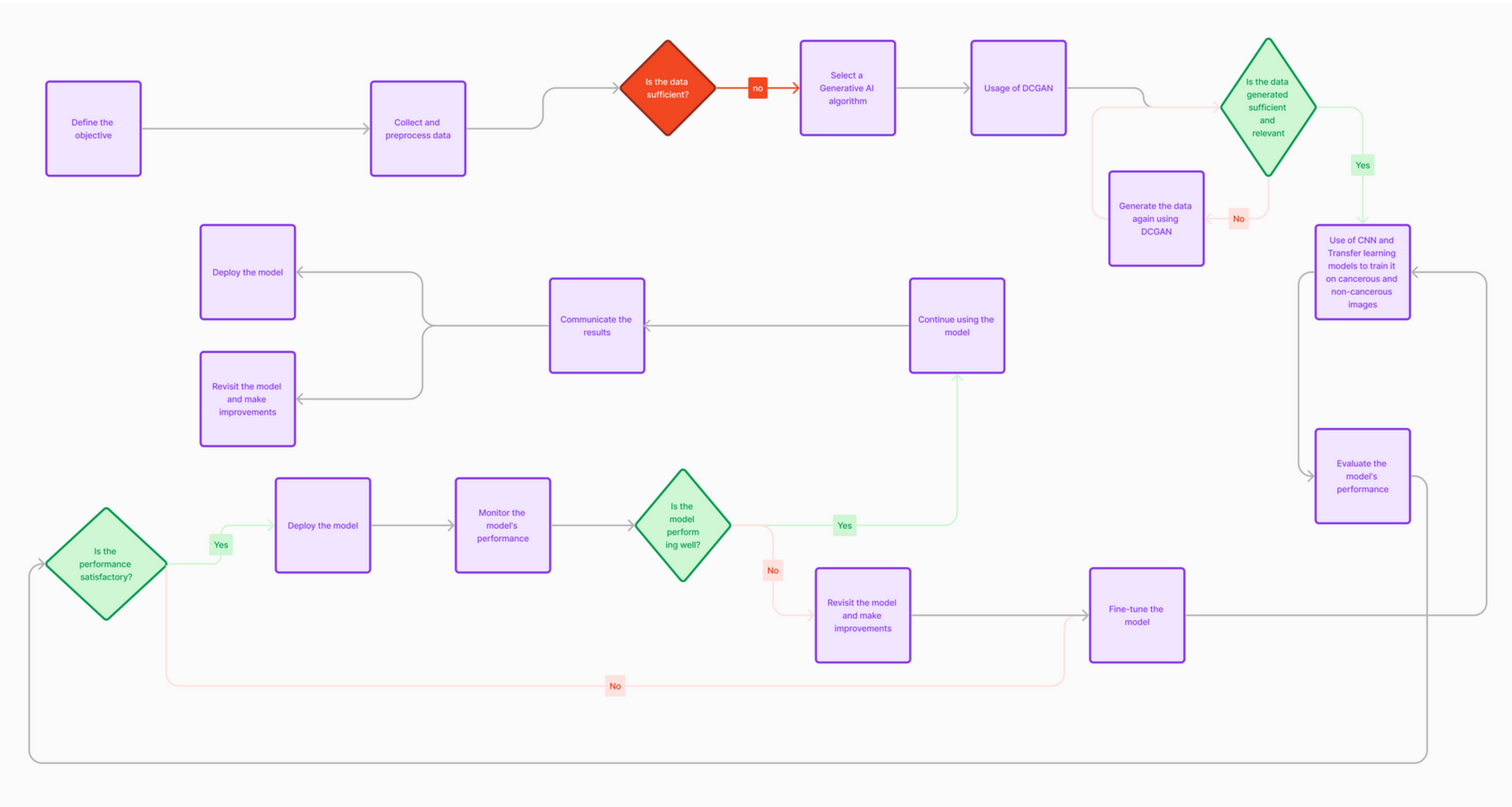
Findings of the survey /Challenges & Limitations of the existing system

- Existing methods (GANs, DCGANs) require large amounts of expensive, high-quality data.
- These methods may struggle to capture full data variations, leading to repetitive outputs.
- Their effectiveness can vary depending on the specific dataset used.
- Some studies lack reader evaluation, limiting real-world insights.
- Limited study scope due to small sample size or specific tasks.
- Regulatory limitations may hinder complete evaluation against existing standards.
- Studies might be limited by small or non-diverse datasets.
- Unexplored crucial settings could potentially improve model performance.

Objectives

- Develop a robust Deep Convolutional Generative Adversarial Network (DCGAN) model for generating realistic synthetic images of breast tissue, encompassing both benign and malignant cases.
- Employ transfer learning techniques to optimize the performance of the classification model for distinguishing between benign and malignant breast tissue.
- Evaluate the effectiveness of synthetic images generated by the DCGAN in improving the accuracy of breast cancer diagnosis.
- Address limitations of existing methodologies, such as dataset scarcity and class imbalance, by leveraging generative AI techniques.
- Enhance the accessibility and affordability of breast cancer diagnosis through the implementation of innovative machine learning approaches.
- Contribute to the advancement of medical image analysis research by exploring the potential of generative artificial intelligence in improving diagnostic capabilities.

Proposed System Architecture



Methodology /Algorithms

1. Generative Adversarial Network (GAN):
    - Objective: This is the core of the project. A GAN will be used to generate synthetic images of breast tissue, encompassing both healthy and cancerous variations.
    - Components: It consists of two competing neural networks:
        - Generator: Learns to create realistic synthetic images by analyzing real breast tissue images.
        - Discriminator: Attempts to distinguish between real and synthetic images, "training" the generator to improve its output.
    - Example: Imagine the generator as an artist trying to paint realistic portraits based on real photos. The discriminator is the art critic, giving feedback to the artist until the paintings are indistinguishable from real photos.

Methodology /Algorithms

2. Transfer Learning:
   - Objective: This technique aims to improve the performance of the classification model by leveraging a pre-trained model on a similar image recognition task.
   - Process: A pre-trained model (e.g., trained on a large dataset of general images) will have its final layers replaced and fine-tuned on the synthetic and real breast tissue images for the specific task of cancer classification.
   - Example: Imagine training a model to recognize different dog breeds. Transfer learning could involve using a pre-trained model that already recognizes general shapes and objects, then fine-tuning it to identify specific dog breed characteristics.

Methodology /Algorithms

3. Image Augmentation:
   - Objective: This technique aims to artificially increase the dataset size and diversity, improving the model's robustness and ability to generalize to unseen data.
   - Methods: Techniques like random flipping, cropping, rotation, and adding noise can be used to create variations of existing images.
   - Example: Imagine having a small dataset of cat pictures. Image augmentation could create flipped, rotated, and slightly blurred versions of these images, essentially increasing the dataset size and variations for the model to learn from.

Modules

Module 1: Data Acquisition and Preprocessing

- Description: This module focuses on collecting real breast tissue images from mammograms or other imaging modalities. The data may come from hospitals or medical image repositories. Preprocessing steps like resizing, normalization, and potential anonymization might be applied.

Modules

Module 2: Generative Adversarial Network (GAN) Training

- Description: This core module involves building and training the GAN. Here's a breakdown of the sub-modules:
  - 2.1: Generator Network Design: This involves defining the architecture of the neural network responsible for generating synthetic breast tissue images. Convolutional layers are likely used to capture spatial features in the images.
  - 2.2: Discriminator Network Design: A separate neural network architecture is built to distinguish real from synthetic images, providing feedback to the generator for improvement.
  - 2.3: GAN Training Process: Both networks are trained iteratively. The generator tries to create ever-more realistic images, while the discriminator refines its ability to identify fakes. This training continues until the generated images become indistinguishable from real ones.

Modules

Module 3: Transfer Learning and Model Fine-tuning

- Description: This module leverages pre-trained models to improve the classification model's performance. Here's the breakdown:
  - 3.1: Pre-trained Model Selection: A pre-trained model on a similar image recognition task (e.g., general image classification) is chosen.
  - 3.2: Model Adaptation: The final layers of the pre-trained model are replaced and fine-tuned using the combined dataset of real and synthetic breast tissue images for the specific task of classifying cancerous and healthy tissue.

Module 4: Image Augmentation

- Description: This module focuses on artificially expanding the dataset and improving its diversity.
  - 4.1: Augmentation Techniques: Techniques like random flipping, cropping, rotation, and adding noise are applied to existing real and synthetic images to create variations, essentially increasing the amount of training data for the model.

Modules

Module 5: Classification Model Training and Evaluation

- Description: This module focuses on training and evaluating the final classification model:
  - 5.1: Model Training: The fine-tuned model from Module 3 is trained on the combined dataset (real and synthetic images) to learn to differentiate between healthy and cancerous breast tissue.
  - 5.2: Model Evaluation: Performance metrics like accuracy, precision, recall, and F1-score are used to assess the model's effectiveness in classifying breast cancer on a separate validation dataset.

Module 6: Result Analysis and Interpretation

- Description: This module involves analyzing the results of the classification model, including:
  - 6.1: Performance Comparison: Comparing the model's performance when trained on real vs. synthetic data, or with and without image augmentation.
  - 6.2: Generalizability Assessment: Evaluating how well the model performs on unseen data to assess its potential for real-world application.

Experimental Set up

Hardware:

- Computing Resources: Powerful computing resources with a dedicated Graphics Processing Unit (GPU) are crucial for training deep learning models like GANs and CNNs. This could be a single high-end workstation with a powerful GPU or a cloud computing platform offering access to GPUs.

Software:

- Deep Learning Frameworks: Popular choices include TensorFlow, PyTorch, or Keras with a backend like TensorFlow or Theano. These frameworks provide tools and libraries for building, training, and deploying deep learning models.
- Programming Languages: Python is the dominant language for deep learning due to its extensive libraries and ease of use. Familiarity with Python and libraries like NumPy (numerical computations) and Pandas (data manipulation) is essential.

Experimental Set up

Software:

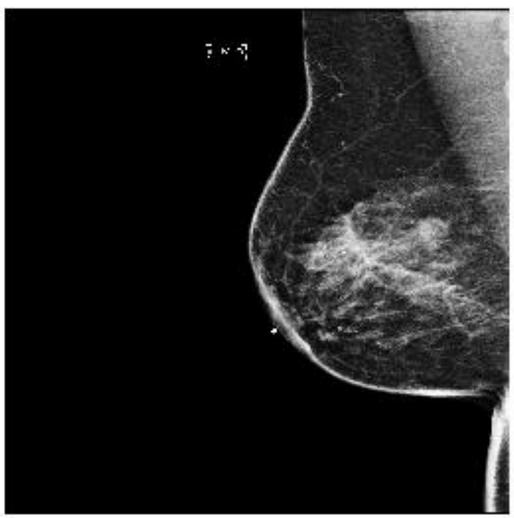
- Data Processing Libraries: Libraries like Scikit-image can be used for image manipulation tasks like resizing and normalization during data preprocessing.
- Visualization Tools: Tools like Matplotlib or TensorBoard can be used to visualize the training process, loss functions, and generated images.

Optional Tools:

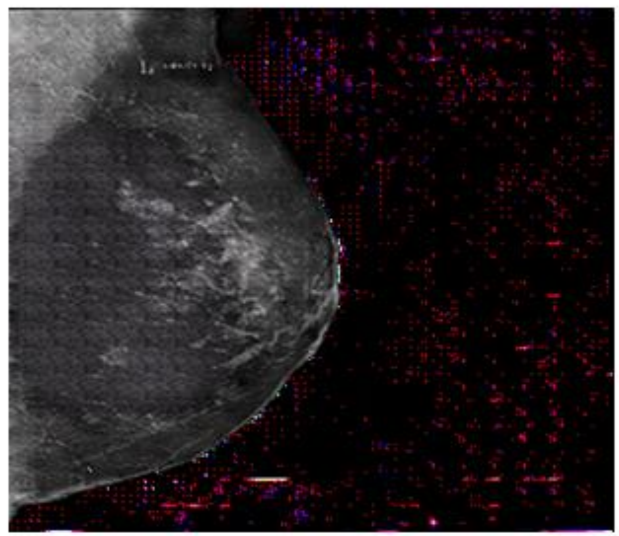
- Cloud Storage: Cloud storage platforms like Google Cloud Storage or Amazon S3 can be used to store and manage large datasets of medical images.
- High-Performance Computing (HPC) Clusters: For very large datasets or complex models, researchers might leverage HPC clusters for parallel processing and faster training.

Results

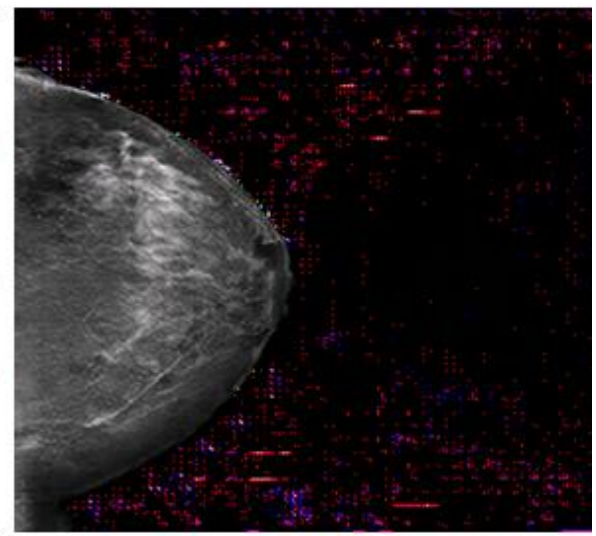
The Images have been generated right now and the model training needs to be done for classification



Real Cancerous Image



Generated Cancerous Images



Generated Cancerous Images

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Paper Status

- Abstract
- Introduction
- Techniques and frameworks
- Proposed approach
    - Dataset description
    - Image generation using DCGAN
    - Convolutional Neural Network for Classification

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