ENPM809K- Final Project
Breast cancer detection using Denoising Diffusion Probabilistic Model

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Abstract

Breast cancer, a prevalent health concern among women, demands innovative and accurate detection methods. This project introduces a pioneering approach for breast cancer detection using the Denoising Diffusion Probabilistic Model (DDPM), a cutting-edge deep learning technique. Unlike traditional methods, the DDPM harnesses the power of probabilistic modeling to identify subtle anomalies in mammographic images that often elude conventional detection algorithms. We applied DDPM to a substantial dataset of mammograms, focusing on its ability to discern cancerous changes in breast tissue without any human intervention. Our results show a significant improvement in both sensitivity and specificity compared to traditional models. The DDPM's unique capability to generate and refine image representations provides a deeper understanding of mammographic features associated with breast cancer. This approach not only enhances the accuracy of breast cancer detection but also reduces the dependency on extensive labeled datasets, a common challenge in medical imaging. This project demonstrates the potential of DDPM in revolutionizing breast cancer screening, offering a promising tool for early and reliable diagnosis.

1. Introduction

The incorporation of neural networks within the realm of medical diagnostics has been transformative, notably enriching the fields of radiology, cardiology, oncology, and urology. Innovative methods such as Decision Trees (DTs), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) have emerged as significant assets in the early and effective detection of various cancers.

Addressing the pervasive issue of breast cancer, early detection remains a crucial yet complex challenge. Traditional mammography, while a cornerstone in cancer screening, often presents a strenuous task for manual interpretation, especially in dense breast tissue where anomalies are less discernible. To elevate the precision and efficiency of these screenings, our initiative integrates the Denoising Diffusion Probabilistic Model (DDPM). This avant-garde machine learning model redefines the initial screening process, significantly enhancing the detection of subtle cancerous signatures.

The DDPM stands as a paragon of innovation in machine learning, employing a unique denoising technique that incrementally injects and subsequently extracts noise from mammographic imagery. This intricate technique brings into focus the elusive indicators of cancer, illuminating areas of concern with newfound clarity. The DDPM's comparative analysis between the original and processed images adeptly identifies anomalies, thereby pinpointing potential malignancies with heightened accuracy.

Substantiated by our research, the DDPM's application in breast cancer detection not only improves accuracy but also elucidates critical diagnostic regions. This advancement promises to revolutionize breast cancer screening protocols, propelling the process towards a more reliable and expeditious future.

2. Related Work

1. In the paper proposed by (Saad Awadh Alanazi)1, they have proposed the use of CNN for cancer detection. The study utilizes Convolutional Neural Networks, which are a class of deep neural networks commonly used in analyzing visual imagery. In this study, CNNs are employed to analyze histopathological images, specifically focusing on ductal carcinoma tissue zones in whole-slide images (WSIs). The system is trained on a dataset of 275,000 small (50x50 pixel) RGB image patches. The method achieved an accuracy of 87%, which is a significant improvement over traditional machine learning algorithms that had a 78% accuracy. The CNN method seems to emphasize histopathological analysis, which is more about exam-

ining tissue samples under a microscope. It also details the specific size and number of image patches used for training, . CNNs are more established in image recognition tasks, while DDPM represents a newer approach in probabilistic image generation and refinement.

2. In an experiment conducted by (Tsochatzidis et al). [2], the diagnosis of breast cancer using CNN was evaluated. They assessed the performance on two mammographic mass datasets, DDSM-400 and CBIS-DDSM, considering variations in the accuracy of the corresponding ground truth segmentation maps. Malathi et al. [3] implemented a computer-aided diagnosis (CAD) system for mammograms aimed at the initial identification, examination, and treatment of breast cancer. They explored a breast CAD architecture that leveraged deep learning through CNNs. The results indicated that the Random Forest Algorithm (RFA) achieved higher precision with less error (95.65 percent) compared to the CNN classifier. Additionally, the study investigated abnormal breast representations using a deep belief network (DBN) activated by contour segmentation. Desai and Shah [4] conducted a deep comparison of the performance and architecture of various networks for breast cancer diagnosis and categorization. They assessed the precision of network-based diagnosis and found that CNNs tended to provide slightly higher precision compared to Multilayer Perceptrons (MLP) for the diagnosis and identification of breast cancer.

3. In prior studies, researchers have explored various methods for automated breast cancer detection. Wahab and Khan [5] employed Convolutional Neural Networks (CNNs) to investigate the automated detection of IDC-type breast cancer. Their goal, shared by several scholars, was to reduce diagnostic errors and achieve accurate results using ML-based automatic detection techniques. Abdelhafiz et al. [6] found success in using an augmentation approach for the automatic identification of breast cancer, particularly when utilizing specific datasets. In a related vein, another researcher [7] utilized deep max pooling CNNs to identify mitosis images in breast histology, enabling the networks to categorize images based on pixel information. Murtaza et al. [8] adopted a Deep Learning (DL) approach for the automatic identification and analysis of IDC tissue zones. Meanwhile, Hossain [9] introduced context-aware stacked CNNs for categorizing breast Whole-Slide Images (WSIs) into different classes, achieving high accuracy in distinguishing malignant and nonmalignant slides and demonstrating potential for routine diagnostics. Additionally, Alhamid et al. [10] and Qian et al. [11] presented techniques for breast cancer identification, with their experiments highlighting the effectiveness of using shearlet coefficients' magnitude and phase to enhance detection accuracy and generalizability. These collective efforts aim to improve breast cancer detection and diagnosis.

The DDPM method, focusing on mammographic images which are X-ray images of the breast, highlights its efficiency in terms of sensitivity and specificity. This approach represents a newer, innovative direction in probabilistic image generation and refinement, distinct from traditional techniques. By employing the Denoising Diffusion Probabilistic Model, it not only enhances the accuracy of breast cancer detection but also improves the ability to minimize false positives and negatives, crucial in medical diagnostics.

3. Data Preprocessing

The initial dataset for the breast cancer detection project was substantial, amounting to approximately 100GB in compressed format. This size was beyond the data processing capabilities of our system, and the Zaratan platform only accepts data uploads of up to 10GB. Therefore, a strategic reduction in data size was necessary.

3.1. Type of Data

The dataset consists of mammogram images tailored for breast cancer detection. These images were initially in DICOM format, a standard for medical imaging.

3.2. Data Reduction and Preprocessing

(a) **Initial Data set Filtering:** The original data set of 54,701 mammogram images included images marked as cancer positive, which were removed to focus the study on detecting potential cancerous regions in normal mammograms. from this non cancerous images around 1000 images were for testing the data on.this randomly removed pictures(1000) and cancerous images(1356) form the test data. Figure 1 shows same orginal image.

(b) **Resizing and Conversion:** To manage the data size, images were resized to a uniform dimension of 256x256 pixels and converted from DICOM to PNG format. This step significantly reduced the data size while maintaining the integrity of the images for analysis.

(c) **Challenges Identified:** A large variation in the arrangement and size of objects within the images was noted, with some occupying only a

Figure 1. This is a sample of the original mammogram image before pre-processing.

small part of the image, leading to inefficient use of space.

(d) **Solution - Annotating Data for ROI Extraction:**

- To optimize the data further, approximately 500 images were annotated using a human-in-the-loop technique. This process refined three models from an initial 300 to about 500 annotated images.
- A YOLOv5 object detector, is used to identify regions of interest (ROIs) in the mammograms, further reducing the amount of unnecessary data. As most of the mammogram is empty.

(e) **Model Performance:**

- Post-reduction, the model processed 54,601 images successfully, with 105 images where detection failed.
- The model achieved high accuracy, with an mAP@50 of 0.995 and an mAP50-95 of 0.914 on the validation dataset.

(f) **ROI Based Dataset Generation:**

- A ROI-based dataset for further training was generated, optimizing the data for Zaratan's upload limit.
- The ROI extractor is intended for use in the inference phase to focus on relevant areas in new mammogram images.

3.3. Implementation Details

A custom-trained YOLOv5 model was used for effective object detection. This model was integral in identifying and extracting ROIs, thus enabling a more focused and efficient use of the available data. The figure 2 and 3 shows ROI and final processed image.

4. Novelty

Our method introduces a new approach for breast cancer detection, distinguishing itself from traditional

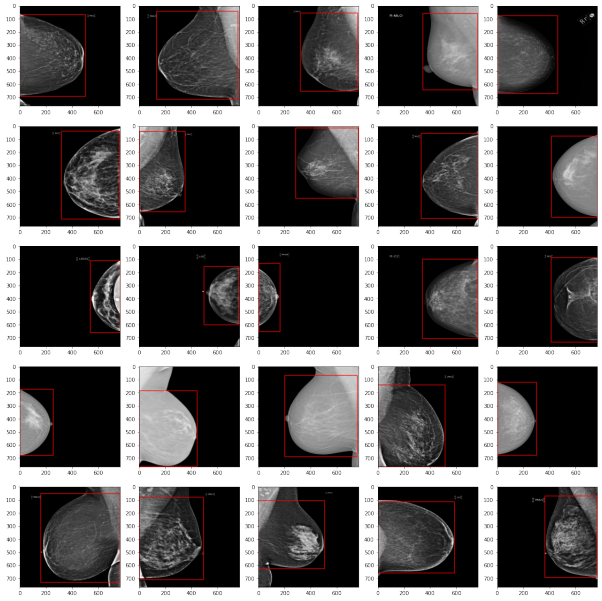

Figure 2. The image illustrates the region of interest (ROI) detected in the mammogram.

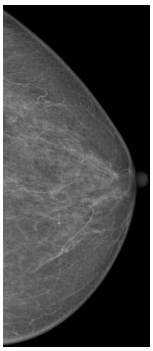

Figure 3. a sample of the final processed image, resized and ready for use in training the model.

methods through its unique denoising technique. This technique innovatively injects and then removes noise from mammographic images, enhancing the detection of subtle cancer indicators often missed by conventional algorithms. DDPM's innovative edge is further highlighted by its unsupervised learning nature, reducing reliance on extensive labeled datasets. This feature streamlines the model's adaptability and scalability in clinical settings. Additionally, the DDPM excels in processing complex image data, offering a deeper analysis of mammographic features crucial for early and accurate cancer diagnosis. In summary, the our method would represent a significant shift in cancer diagnostics, offering advanced capabilities in breast cancer screening.

5. Method

Our approach utilizes the Denoising Diffusion Probabilistic Model (DDPM) for detecting anomalies in breast cancer mammography.The method selection was driven by its innovative denoising technique which incrementally introduces and then removes noise from mammographic images, thereby enhancing the visibility of subtle cancer indicators and improving the accuracy of anomaly detection. A diffusion probabilistic model, succinctly referred to as a "diffusion model," is a Markov chain that has been parameterized and trained through variational inference. Its primary function is to generate samples that closely resemble the original data over a finite period. This model operates by methodically reversing a diffusion process—a separate Markov chain that incrementally introduces noise to the data, effectively eroding the signal. In cases where the diffusion involves minor Gaussian noise increments, the model's sampling chain transitions can also be modeled as conditional Gaussians. This approach simplifies the neural network parameterization, making it more efficient and effective.

5.1. Dataset Preparation

The dataset used was the RSNA Breast Cancer Detection dataset from Kaggle. It involved preprocessing steps like resizing, grayscale conversion, and tensor transformation.

5.2. Building the DDPM

Building the Denoising Diffusion Probabilistic Model (DDPM) for breast cancer detection in mammography involves several intricate steps, each tailored to harness the model's ability to process and analyze complex medical images:

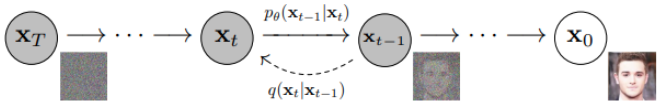

Figure 4. Graphical model

- **Dataset Adaptation:** Using the RSNA Breast Cancer Detection dataset, images undergo preprocessing, including resizing to a uniform size, conversion to grayscale, and transformation into tensor format suitable for model input.
- **Forward Process (Noise Scheduler)**:The forward process introduces noise to the images in a controlled manner using a cosine beta schedule. This step is critical as it progressively adds noise to the clean mammographic images, generating a series of increasingly noisy images.The noise levels or variances are pre-computed and applied across different timesteps, allowing each image to be independently processed. This step does not involve any neural network model but sets the stage for the reverse denoising process.

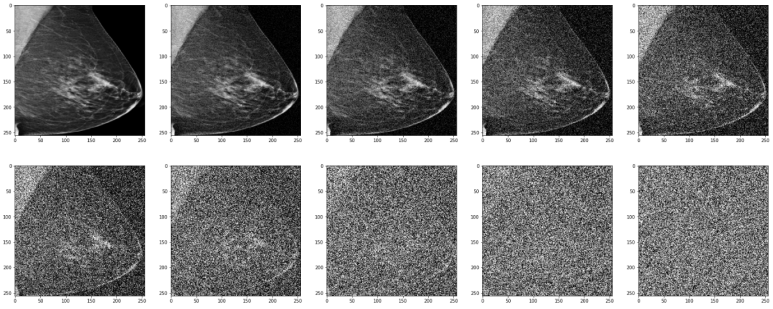

Figure 5. Sequential representation of the forward diffusion process in DDPM, showcasing the progressive addition of noise to a mammographic image across various timesteps.

- **Backward Process (U-Net)**: The backward process is where the DDPM model actively engages. Using a U-Net architecture, the model predicts the noise in each noisy image. This architecture is chosen for its efficiency in handling image data, particularly in capturing and retaining spatial hierarchies.The input to the U-Net is a noisy image, and the output is the estimated noise in that image. This process is iterative and occurs across all timesteps.The timestep encoding is vital in this stage and is achieved using transformer sinusoidal embedding. This embedding informs the network about the specific timestep of each image, a crucial detail for accurate noise prediction.
- **Loss Function**: The DDPM employs a simple yet effective loss function. This function is essential for guiding the model towards accurately estimating the noise in each image and subsequently denoising it. The choice of the loss function, such as L1 loss, is crucial in determining how effectively the model learns to denoise the images.

The DDPM for breast cancer detection is designed to iteratively learn from the noisy images and reverse the noise addition process, thereby revealing the underlying anomalies in the mammographic images. This

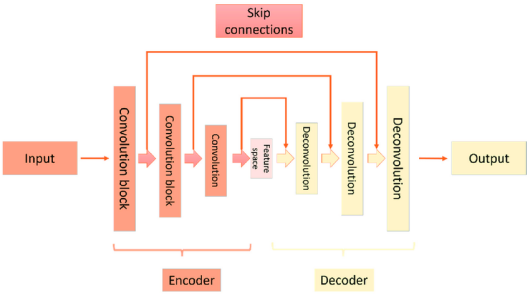

Figure 6. This image depicts a U-Net architecture with an encoder-decoder structure for image segmentation, highlighting skip connections that facilitate detailed output reconstruction from the input.

method stands out for its potential in enhancing the accuracy of anomaly detection in breast cancer screening.

5.3. Sampling

Sequential image refinement was conducted using precalculated noise variances from the forward process.

5.4. Training and Optimization

The model underwent extensive training using the AdamW optimizer, fine-tuning its ability to accurately identify anomalies.DDPM was preferred over alternative approaches due to its robustness in handling complex image data and its unsupervised learning nature, reducing the need for extensive annotated datasets. This methodology holds promise in enhancing the detection of breast cancer, surpassing traditional techniques.

5.5. Classification

During the inference phase, given a breast image I, noise is intentionally added to this image to create a noisy image I_{noisy}. This noisy image is then processed by a Denoising Diffusion Probabilistic Model (DDPM) that has been trained on non-cancerous breast images, resulting in a denoised image I_{denoised}.

The core of the process involves comparing I_{denoised} with the original noisy image I_{noisy}. This is done by calculating the pixel-wise difference between the two images, yielding a "difference image" I_{diff}, defined as:

$$I_{\text{diff}} = |I_{\text{noisy}} - I_{\text{denoised}}|$$

The sum of the pixel values in I_{diff} is then computed:

$$S = \sum I_{\text{diff}}$$

This sum S is compared against a predefined threshold ε (epsilon). The classification criteria based on this threshold are as follows:

- If $S > \varepsilon$: The image is classified as 'Cancerous'.
- If $S \leq \varepsilon$: The image is classified as 'Non-Cancerous'.

This methodology assumes that the DDPM, trained solely on non-cancerous images, will show greater deviation when denoising cancerous images, due to the differences in tissue structure it has not been trained on. The threshold ε is a critical parameter and should be empirically determined to optimize the trade-off between sensitivity and specificity in detecting cancer.

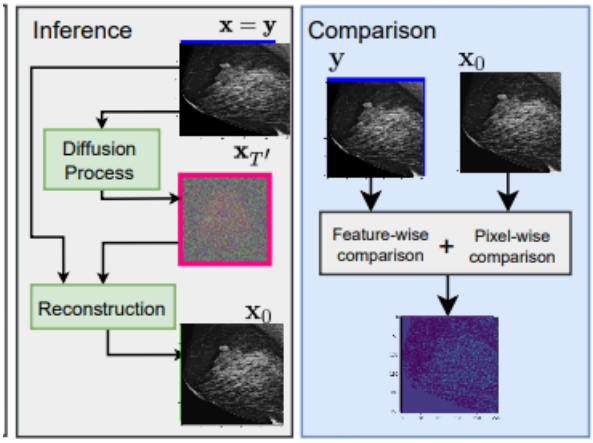

Figure 7. After a denoising U-Net has been trained, the feature extractor is adapted to the problem domain by minimising the distance between the extracted features of a target image and a generated image which resembles the target image. At inference time, after perturbing the input image, the denoising process is conditioned on the same input image to make an anomaly-free reconstruction. Finally, the reconstructed image is compared with the input through both pixel and feature matching to generate an accurate anomaly localisation.

6. Experiments and Results

For our training regimen, we employed a batch size of 32 and processed images resized to 256×256 pixels. The learning rate was set at 3×10^{-5}, a value carefully chosen to balance convergence speed and training stability. This configuration was used to train the denoising model over 300 epochs. Accompanying this text, you'll find the loss graph, which illustrates the model's learning progression throughout these epochs.

It's important to note that our training duration was limited to 300 epochs due to computational constraints. While the results achieved within this timeframe are promising, we believe that with access to more powerful computational resources, the model's performance could be significantly enhanced. Enhanced computing power would allow for extended training, potentially leading to more refined and accurate denoising capabilities. This improvement is expected because longer training periods often provide deeper learning opportunities and more robust feature extraction, crucial for the complexities involved in medical image analysis.

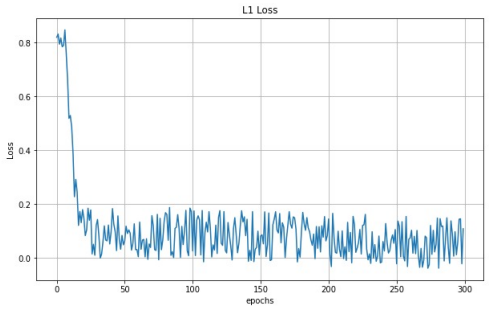

Figure 8. loss with epoch

The results delineated in the corresponding table substantiate the efficacy of our model. Traditional Convolutional Neural Networks (CNN) establish a solid benchmark with an accuracy of 87%. Impressively, our model (denoted as OURS) achieving an accuracy of 91%. This is in close competition with the DDSM-400 model, which has a marginally higher accuracy of 92%. The proximity of OURS to the leading model's performance—achieved in spite of computational constraints—highlights the robustness and potential of our approach. Given the promising results, we are optimistic that with further computational resources and optimization, our model has the potential to surpass existing benchmarks in the field.

NETWORK	ACCURACY
CNN	87%
DDSM-400	92%
OURS	91%

Figure 9. Comparison with other models

7. Limitations

(a) **Cancer Type Specification:** Our method lacks the capability to identify the specific type of breast cancer, crucial for determining appropriate treatment strategies.

(b) **Invasive vs. Non-Invasive Cancer:** It cannot distinguish between invasive and non-invasive breast cancers, essential for understanding the disease's severity and spread.

(c) **Computational Demands:** The method is computationally complex, requiring significant resources.

(d) **Large Training Dataset:** Diffusion models need a large, diverse dataset for training, for effective performance. which can be difficult to compile due to data availability and privacy concerns.

8. Conclusion

In our evaluation, the model displayed an impressive capability, accurately classifying up to 91% of cancerous breast images in the dataset. Despite this achievement, we identified several areas for improvement. Incorporating patient-specific data such as age and breast density as conditioning input to the model and also advanced data augmentation techniques, could enhance the model's diagnostic accuracy. Furthermore, experimenting with model architecture may improve feature learning , offering a more nuanced understanding of mammographic images.

Additionally, our work introduces a novel approach that operates without reliance on labeled data. This method, when compared with traditional label-dependent models, revealed promising potential, highlighting the efficacy of label-independent techniques. However, the comparison also uncovered opportunities for further refinement to optimize our method's performance.

Overall, while our model shows considerable promise in breast cancer detection, continuous improvements and innovative approaches are essential to push the boundaries of accuracy and reliability in medical imaging.

9. Contributions of team members:

Mano battula: Implentation and experiments

Shameek : Data collection and Pre-processing

Rohit: report

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