Project Proposal for CS 184A/284A, Fall 2023

**Project Title: Detect, Segment and Classify Breast Ultrasound Images**

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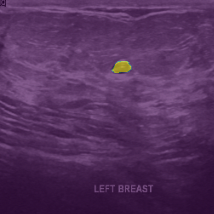
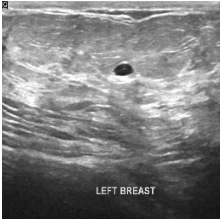
**1. Project Summary**This project aims to find the method to detect, segment and classify breast ultrasound images for breast cancer. This will provide data on the existence of lesions, types and size and shape of lesions to efficiently screen breast cancer. The data comprises breast ultrasound images from 600 patients among women in ages between 25 and 75 years old. Faster R-CNN model will be a baseline model, and we will examine different methods to improve the performance using U-Net, a CNN model specifically for medical images, and MedSAM, a vision transformer trained on medical images. We will evaluate the performance of models by precision, recall, and F1 score for classification and segmentation. Also, we’ll use IoU to evaluate the quality of segmentation.

**2. Problem Definition**The goal of this project is to be able to detect or segment abnormal lesions of breasts from ultrasound images, and also classify a type of lesion if there were any. The two main questions we will be answering are, 1) Does the usage of segmentation, instead of detection, perform better with classifying types of lumps in breast ultrasound and 2) if segmentation works better for classifying types of lesions, then which model of segmentation works better. 3) In the context of breast ultrasound images, does the transformer-based segmentation approach demonstrate superior accuracy and efficiency compared to other segmentation models? Breast cancer is the most common cancer in women in the United States and the second leading cause of cancer death in women [1]. Like any other cancer, early detection is a key, and it is recommended to start screening every year for average women 45 or older [2]. We hope to bolster the process of breast cancer diagnosis with the newest technologies in three different measures. First, Detection provides assistance by informing which images need extra attention to be read, which can allow radiologists to efficiently put their effort into reading. Similarly, classification also supports radiologists with efficient workflow by providing a prediction of results. Lastly, segmentation provides quantitative information about the size and shape of lesions, allowing patients and medical professionals to track the changes of lesions over time and also provide numerical data to further analyze the lesions. Due to its importance, there have been numerous studies done on the topic of computer-aided image analysis for breast cancer diagnosis. According to [3], the most widely used method in classifying breast cancer is CNN at the time of publishing in December 2021 since it can extract useful features from images. In this project, we will also utilize CNN methods, but will be utilizing the state-of-the-art segmentation models. There has been minimal research conducted on these models due to their novelty; however, the available studies, such as [4], [5], [6], delve into the challenges associated with segmenting complex boundaries.

**3. Proposed Technical Approach**

* **Faster R-CNN :** We will use Faster R-CNN for detection and classification, and set the result as a reference. And for this approach, we’ll first transform the mask into bounding boxes of the input data and then apply object detection techniques.
* **Mask R-CNN:** We plan to use Mask R-CNN for segmentation and classification. This approach will serve as a benchmark against which we will evaluate the performance of other segmentation models. Mask R-CNN extends Faster R-CNN by adding a branch for predicting segmentation masks on each Region of Interest (RoI), enabling precise object detection and pixel-level instance segmentation.
* **UNet:** U-Net is a biomedical image segmentation algorithm which assigns class labels to each pixel and identifies the object boundaries. Through convolution and symmetrical deconvolution paths, U-Net model extracts feature maps from the images and localizes each feature within the image. We will be able to know the location distribution of the cancer in the image as well as the category of the image.
* **MedSAM:** MedSAM [7] is a specialized model for medical image segmentation, derived from SAM. SAM, based on a vision transformer, excels in segmentation but faces challenges with medical images due to their distinct characteristics. To overcome this, MedSAM is trained on a vast dataset of over a million medical image-mask pairs. Leveraging MedSAM, we will segment the lesions and further differentiate benign and malignant lesions.
* **Neural Network Classification:** Following the detection and segmentation of lesions, we will develop a classifier to distinguish between benign and malignant lumps. It aims to examine to which additional information derived from segmentation enhances the precision in classifying the nature of identified objects.

**4. Data Sets**The data[[1]](#footnote-0) collected at baseline include breast ultrasound images among women in ages between 25 and 75 years old. This data was collected in 2018. The number of patients is 600 female patients. The dataset consists of 780 images with an average image size of 500\*500 pixels. The images are in PNG format. The ground truth images are presented with original images. The images are categorized into three classes, which are normal, benign, and malignant. Below is the example of the original input image and the image with mask.



**5. Experiments and Evaluation**

In our experiment, we plan to comprehensively evaluate and compare the performance of following models: Faster R-CNN, Mask R-CNN, UNet, and MedSAM, in the context of medical image detection, segmentation and classification tasks. Each model will be trained on a splitted dataset after data augmentation.

For evaluating those models in the context of breast ultrasound images, we will adopt a combination of precision, recall, and F1 score. Additionally, we will use Intersection over Union (IoU) for segmentation quality. Precision will gauge the correctness of the positive predictions, while recall will assess how well our model identifies all relevant cases. The F1 score, a harmonic mean of precision and recall, will provide a balance between the two, offering a single measure of overall accuracy. In segmentation, IoU will be used to quantify the overlap between the predicted and ground truth masks, offering a clear measure of how well our model delineates the boundaries of objects. This comprehensive set of metrics will ensure a thorough evaluation of both the classification and segmentation aspects of our models, providing a robust assessment of their performance.

**6. Software**We will basically use Python and publicly-available codes from Github. (1) For publicly-available codes, we will utilize the open source codes of the Faster R-CNN, Mask R-CNN, U-Net, and MedSAM models and add modifications to them considering the characteristics of our data. (2) For codes we will write ourselves, we will use some codes to preprocess the data (noise cleaning, augmentation, etc.), visualize the results of each model and evaluate its performance.

**7. Milestones**Week 8: Data preprocessing

Week 9: Model training for detection (Faster R-CNN and Mask R-CNN) or segmentation (U-Net and MedSAM), then classification

Week 10: Evaluation and final write-up

**8. Individual Student Responsibilities**

**Sohyun:** Will assist data augmentation, and write and test the code for vision transformer (MedSAM) to train a model for segmentation and classification. Will perform experiments and interpret results for the final report and write the final report.

**Yujeong**: Will write codes and test the U-Net model for segmentation and classification, will interpret results and evaluate the accuracy of the model, will assist to evaluate and compare each algorithm, will write the final report.

**Xinyu:** Will acquire and preprocess the data set to train the algorithms, including data splition and augmentation. Will apply and evaluate detection model (Faster R-CNN) and segmentation model (Mask R-CNN), will assist in writing project reports.

**9. Citation**

[1] American Cancer Society, “Breast Cancer Statistics | How Common Is Breast Cancer?,” *www.cancer.org*, Jan. 12, 2023. https://www.cancer.org/cancer/types/breast-cancer/about/how-common-is-breast-cancer.html

[2] American Cancer Society, “ACS breast cancer screening guidelines,” *www.cancer.org*, Jan. 14, 2022. https://www.cancer.org/cancer/types/breast-cancer/screening-tests-and-early-detection/american-cancer-society-recommendations-for-the-early-detection-of-breast-cancer.html

[3] M. F. Mridha *et al.*, “A Comprehensive Survey on Deep-Learning-Based Breast Cancer Diagnosis,” *Cancers*, vol. 13, no. 23, p. 6116, Dec. 2021, doi: https://doi.org/10.3390/cancers13236116.

[4] M. Hu, Y. Li, and X. Yang, “BreastSAM: A Study of Segment Anything Model for Breast Tumor Detection in Ultrasound Images” *arXiv.org*, May 21, 2023. https://arxiv.org/abs/2305.12447 (accessed Oct. 23, 2023).

[5] Muhammad Azaz Farooq, Z. Gong, Y. Liu, M. Zubair, A. Manzoor, and G. Zhang, “Breast cancer detection from ultrasound images using attention U-nets model” *Fourteenth International Conference on Digital Image Processing (ICDIP 2022)*, Oct. 2022, doi: https://doi.org/10.1117/12.2643599.

[6] M. Ahmadi *et al.*, “Comparative Analysis of Segment Anything Model and U-Net for Breast Tumor Detection in Ultrasound and Mammography Images” *arXiv.org*, Jun. 21, 2023. https://arxiv.org/abs/2306.12510 (accessed Sep. 07, 2023).

[7] J. Ma and B. Wang, “Segment Anything in Medical Images,” *arXiv.org*, Apr. 24, 2023. https://arxiv.org/abs/2304.12306

[8] W. Al-Dhabyani, M. Gomaa, H. Khaled, and A. Fahmy, “Dataset of breast ultrasound images,” *Data in Brief*, vol. 28, p. 104863, Feb. 2020, doi: https://doi.org/10.1016/j.dib.2019.104863.

[9] S. Gokhale, “Ultrasound characterization of breast masses,” *Indian Journal of Radiology and Imaging*, vol. 19, no. 3, p. 242, 2009, doi: https://doi.org/10.4103/0971-3026.54878.

1. <https://www.kaggle.com/datasets/aryashah2k/breast-ultrasound-images-dataset> [↑](#footnote-ref-0)