Screening mammography. Breast cancer is the most common cancer in women and it is the main cause of death from cancer among women in the world 1 . Screening mammography has been shown to reduce breast cancer mortality by 38–48% among participants 2 . In the EU 25 of the 28 member states are planning, piloting or implementing screening programs to diagnose and treat breast cancer in an early stage3 . During a standard mammographic screening examination, X-ray images are captured from 2 angles of each breast. These images are inspected for malignant lesions by one or two experienced radiologists. Suspicious cases are called back for further diagnostic evaluation.

Automatic lesion segmentation in mammography images assists in the diagnosis of breast cancer, which is the most common type of cancer especially among women. The robust segmentation of mammography images has been considered a backbreaking task due to: i) the low contrast of the lesion boundaries; ii) the extremely variable lesions' sizes and shapes; and iii) some extremely small lesions on the mammogram image. To overcome these drawbacks, Deep Learning methods have been implemented and have shown impressive results when applied to medical image segmentation. This work presents a benchmark for breast lesion segmentation in mammography images, where six state-of-the-art methods were evaluated on 1692 mammograms from a public dataset (CBIS-DDSM), and compared considering the following six metrics: i) Dice coefficient; ii) Jaccard index; iii) accuracy; iv) recall; v) specificity; and vi) precision. The base U-Net architectures were trained with a combination of the cross-entropy and Dice loss functions. Although the networks presented Dice scores superior to 86%, two of them managed to distinguish themselves. Clinical Relevance--- The presented comparative study allowed to identify the current performance of deep learning strategies on the segmentation of breast lesions.

Image data:

Please explain about the image data and you know how it's looking looking from image to image and also the comparison of breast parenchyma composition. The detection of lesion will be varing from view to view . In some cases the lesion will be very speculated and it had to be spiculated

Model Development :

The detection of lesion is considered 2 individual architectures one represents the object detection and other represents the segmentation. the object detection is is based on the retinanet model which train on the positive data and negative images majorly not used. The detected bounding box is passed through the segmentation model off unet for the segmentation this we have a segmented region of lesion

The retina net model

the model is trained on the default imagenet weights and the backbone the resnet-50 is used further detection Process. The pretend weights of the imagenet used to get it better accuracy. The model is trained on positives images With only single class.

the output of the return model will be a list of individual counters representing now legion class , probability , the bounding box coordinates Each bounding box coordinates are taken and neighboring cells of 256 it seems are added to the bounding box that resulted array is passed to the unet model

FP

During this the result of grandular tissue and also nipple regions I detected as in false positive so in order to increase your training and also the performance and other model is chosen based on the unet architecture

The main reason for choosing a different architecture instead of the same training on due to the fact sort of limited training data that's been consistently used over oversampling so inorder maximize the segmentation proces.

UNET :

For the region detection an unet segmentation model is considered cause due to the simpler design in adding the negative images during the training process. The unet segmentation model is of x layers with downsampling and upsampling layer with a droput of x range,

The filter used in the model are x,x,x filter with the downsampling and using the same with x filter of upsampling the features. For the downsampling the maxpool is used with x kernal size, With all this together the architecture has x traniable parameters and x non trainable paramaters .

For each filter of the relu activation is used in the hidden layers for the last layer the activation is sigmoid. The segmatation model is of consider the image size of x is fed to the model, the output is a region of the lesion segmentation.

the model is trained on X images and later on tested on the cases of public data and private data oh by the radiologist he he just he does the uses about this he goes