Medical Image Processing with Deep Learning

----Mammograms Classification and Automatic Tumor detection

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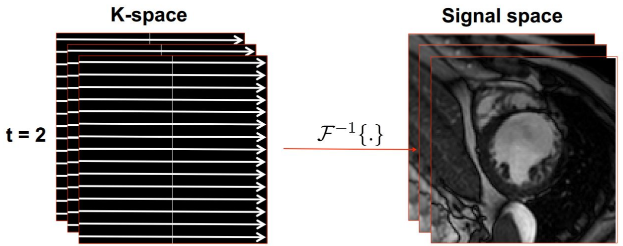
Background

- Why do we use deep learning in medical imaging?
- Why do we study mammograms?

Deep learning in Medical Imaging

- Accelerate data acquisition process
  - use part of k-space data in MRI image reconstruction
- Enhance image resolution
  - low resolution -> high resolution
- Aid disease diagnosis
  - manpower
  - time

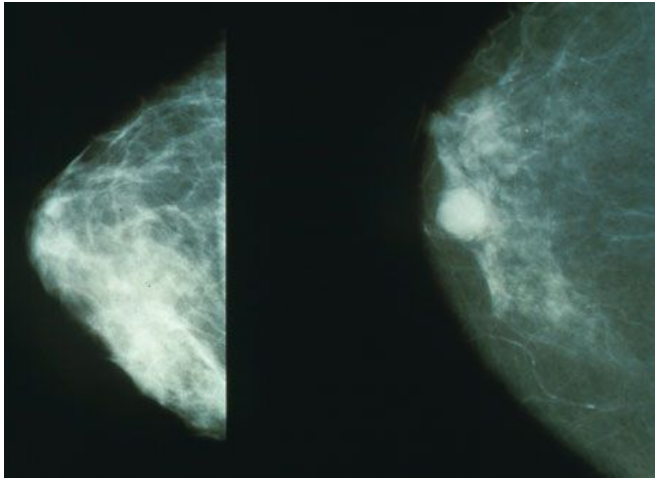


input

output

Mammograms

- Breast cancer is the most common cancer in women and it is the main cause of death from cancer among women in the world.
- Mammography is the process of using low-energy X-rays to examine the human breast for diagnosis and screening.

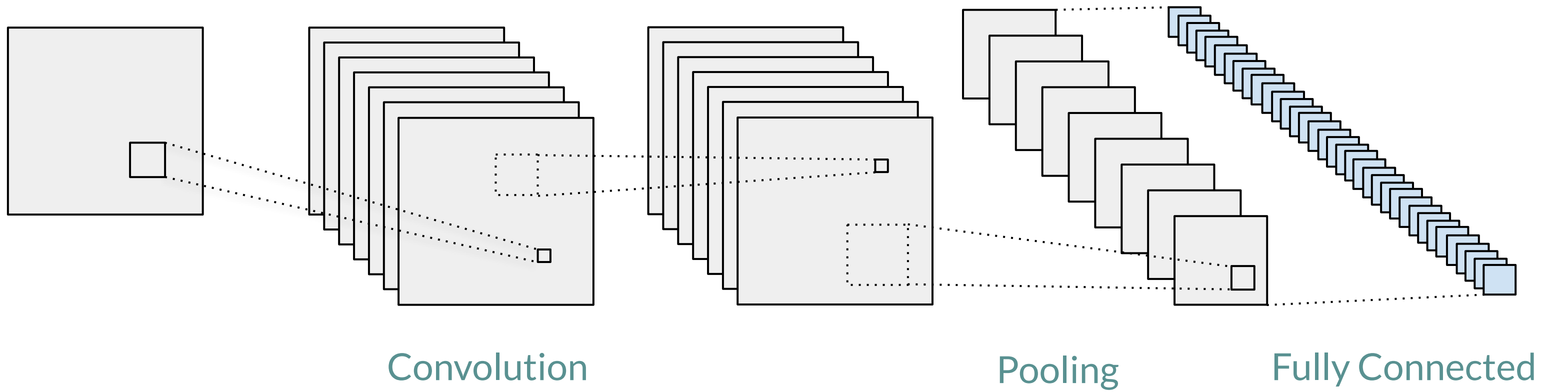


Normal Malignant

Goals

- Classify mammograms into three classes, normal, benign and malignant (CNNI-BCC)
- Automatically detect the tumor without prior information of the presence of a cancerous lesion (IDBLL)

Convolutional Neural Network Improvement for Breast Cancer Classification (CNNI-BCC)



Dataset and Data Augmentation

Dataset: mini-MIAS database of mammograms

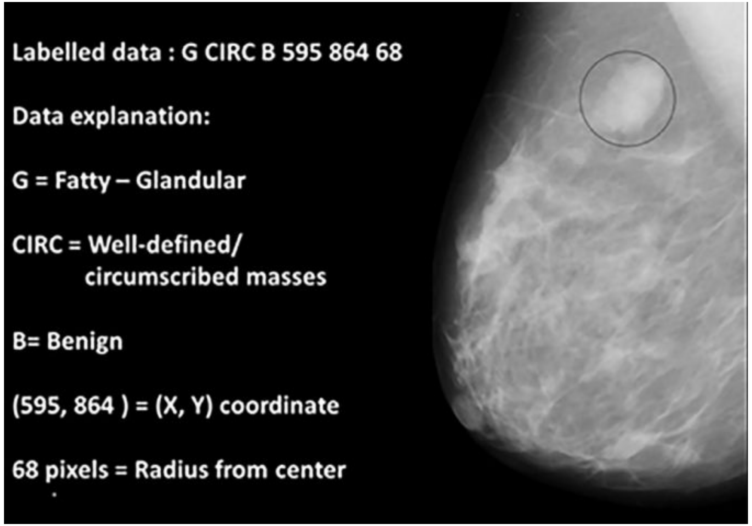
- 322 images in total

Data Augmentation:

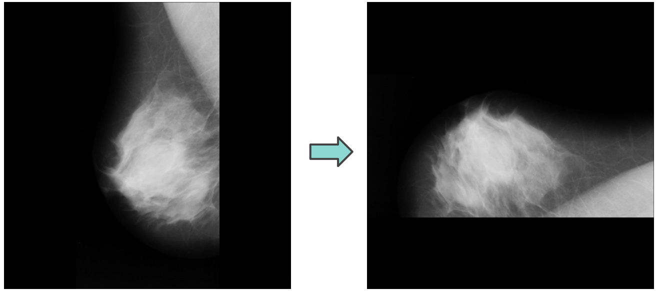
- Rotation (by 90, 180, 270 degrees respectively)
- Flip (vertically)
- Sampling (1024×1024 -> 128×128)

Dataset - mini-MIAS

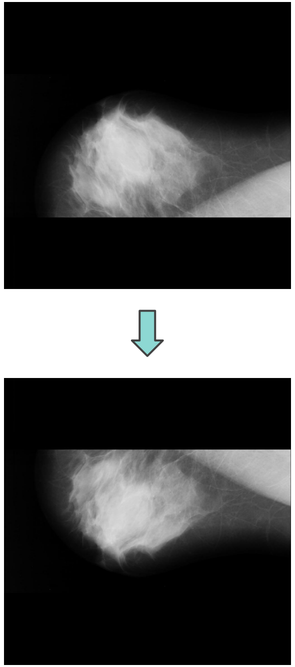
- Labelled
- Has information about the coordinates of tumor center
- Has information about the radius of the tumor



Data Augmentation - Flip/Rotation



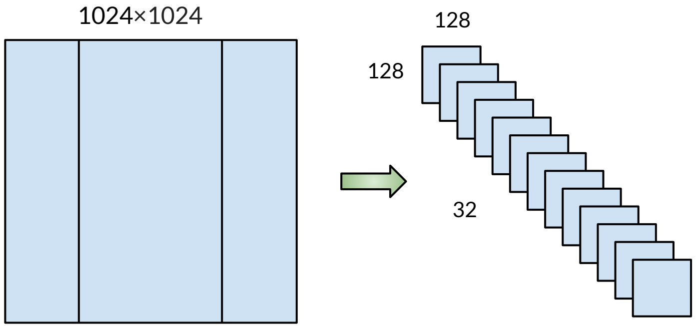
Rotation (90 degrees)



Flip

Data Augmentation - Sampling

- Cut each image equally into 64 image patches
- Select only the middle 4 columns -> Get 32 image patches out of 1 image

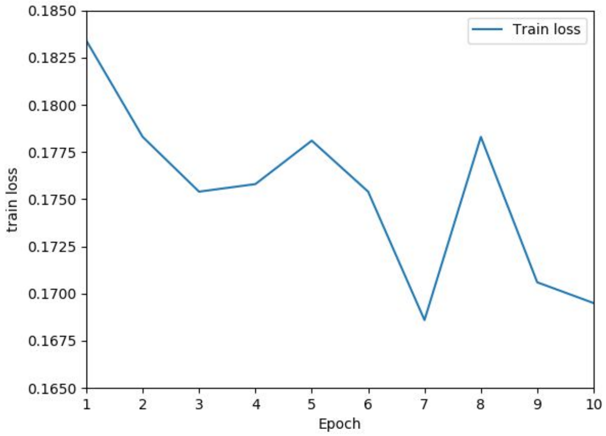


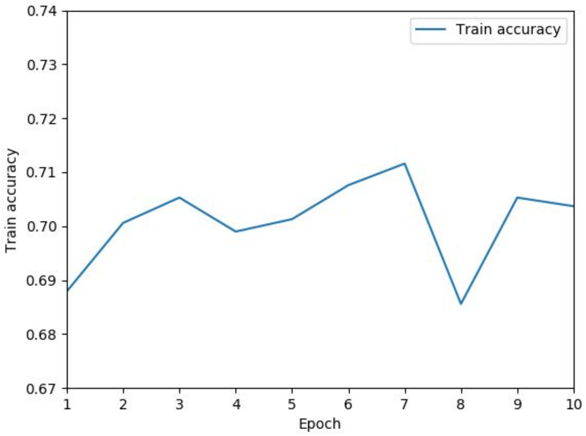
Experiments

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 64, 64, 32)	320
depthwise_conv2d_1 (DepthwiseConv2D)	(None, 64, 64, 32)	32800
conv2d_2 (Conv2D)	(None, 64, 64, 64)	2112
depthwise_conv2d_2 (DepthwiseConv2D)	(None, 32, 32, 64)	262208
average_pooling2d_1 (AveragePooling2D)	(None, 8, 8, 64)	0
flatten_1 (Flatten)	(None, 4096)	0
dense_1 (Dense)	(None, 3)	12291

Total params: 309,731
Trainable params: 309,731
Non-trainable params: 0

Results

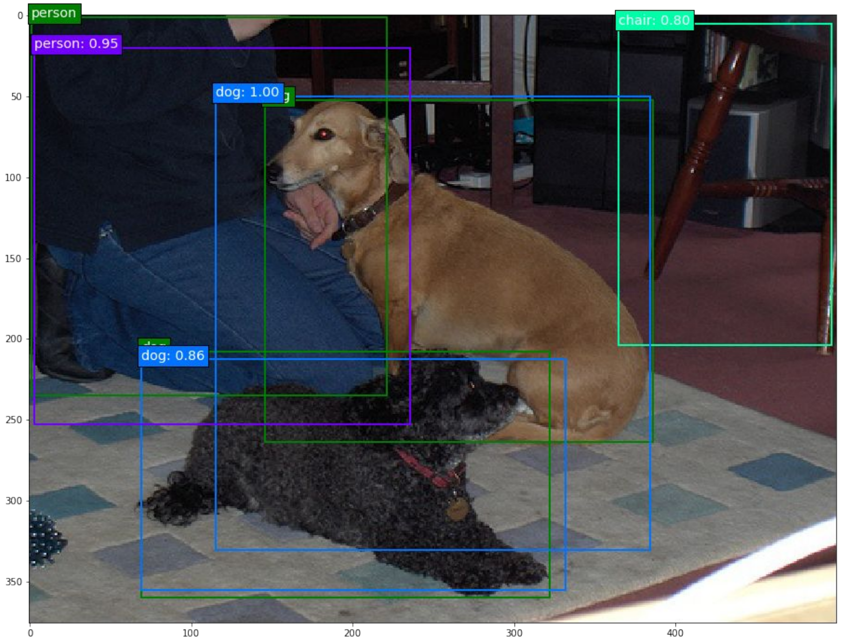


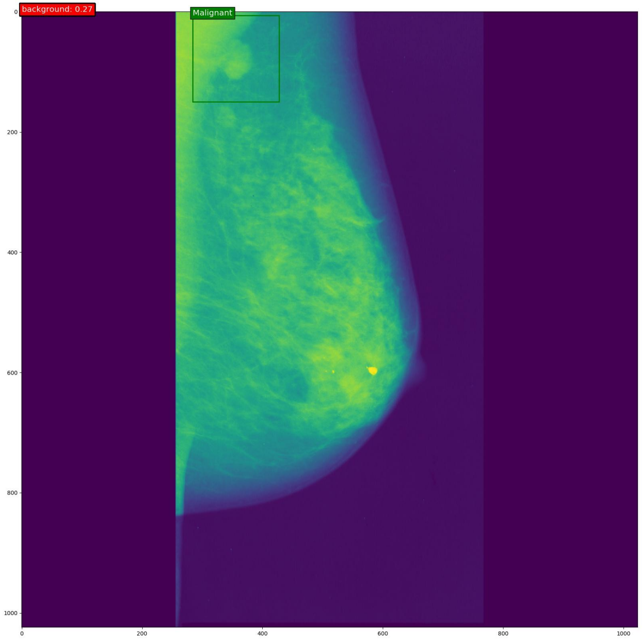


The loss on the test set is: 0.14544324301610326

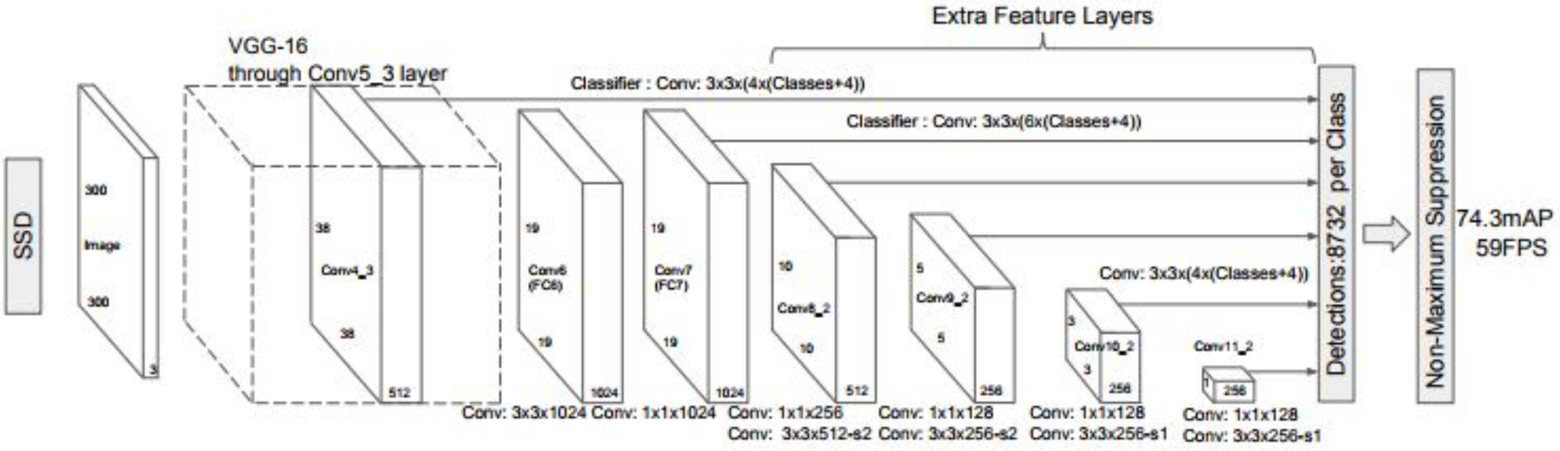
The accuracy on the test set is: 0.7324840809888901

Interactive Detection Based Lesion Locator (IDBLL)





Structure of Single Shot MultiBox Detector (SSD)



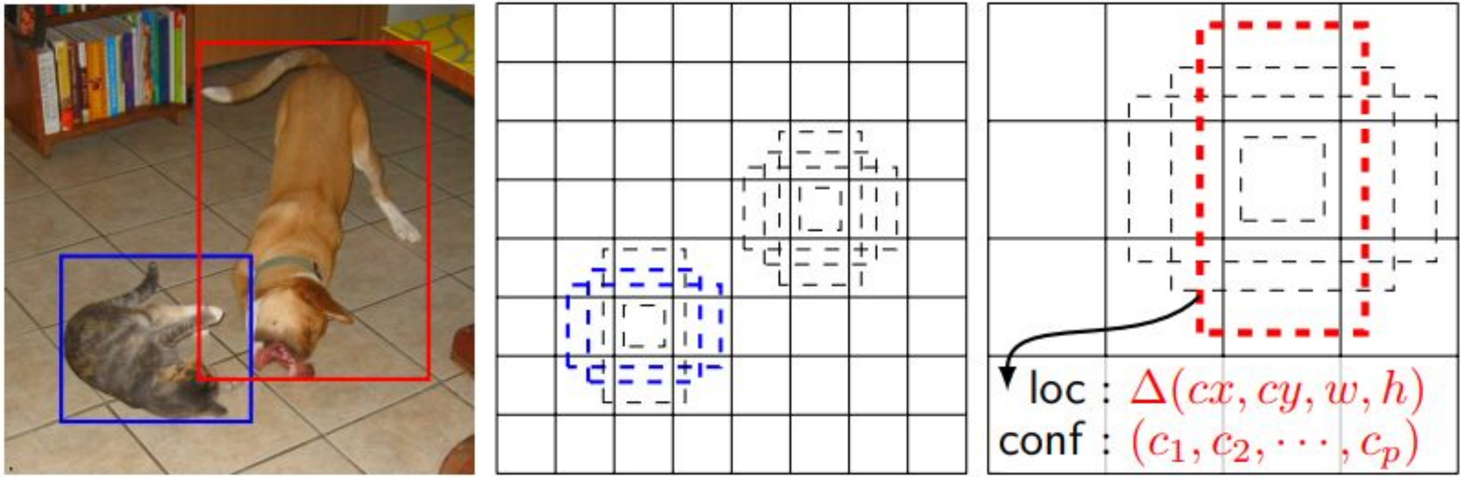
Base Network for classification

+ Multi-scale feature maps for detection

+ Convolutional predictors for detection: multiple classes confidences

+ Default boxes and aspect ratios: localization

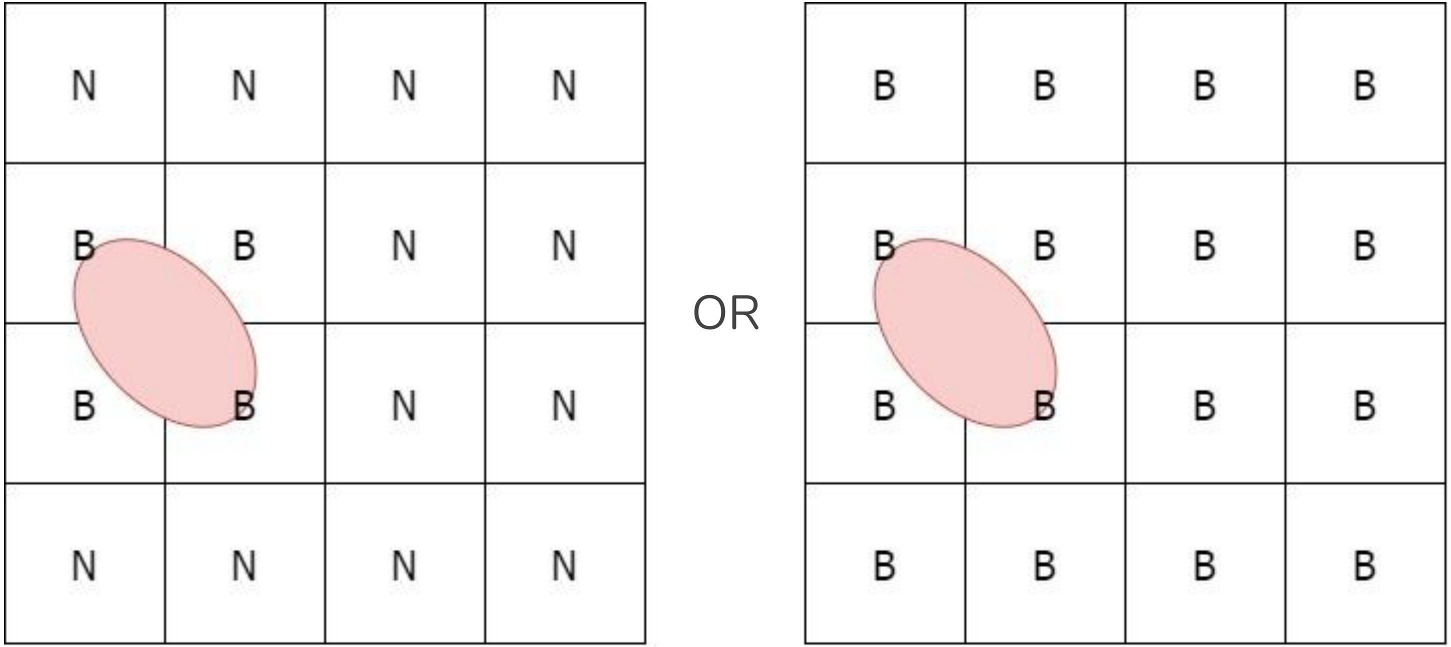
Objective Loss Function



(a) Image with GT boxes (b) 8×8 feature map (c) 4×4 feature map

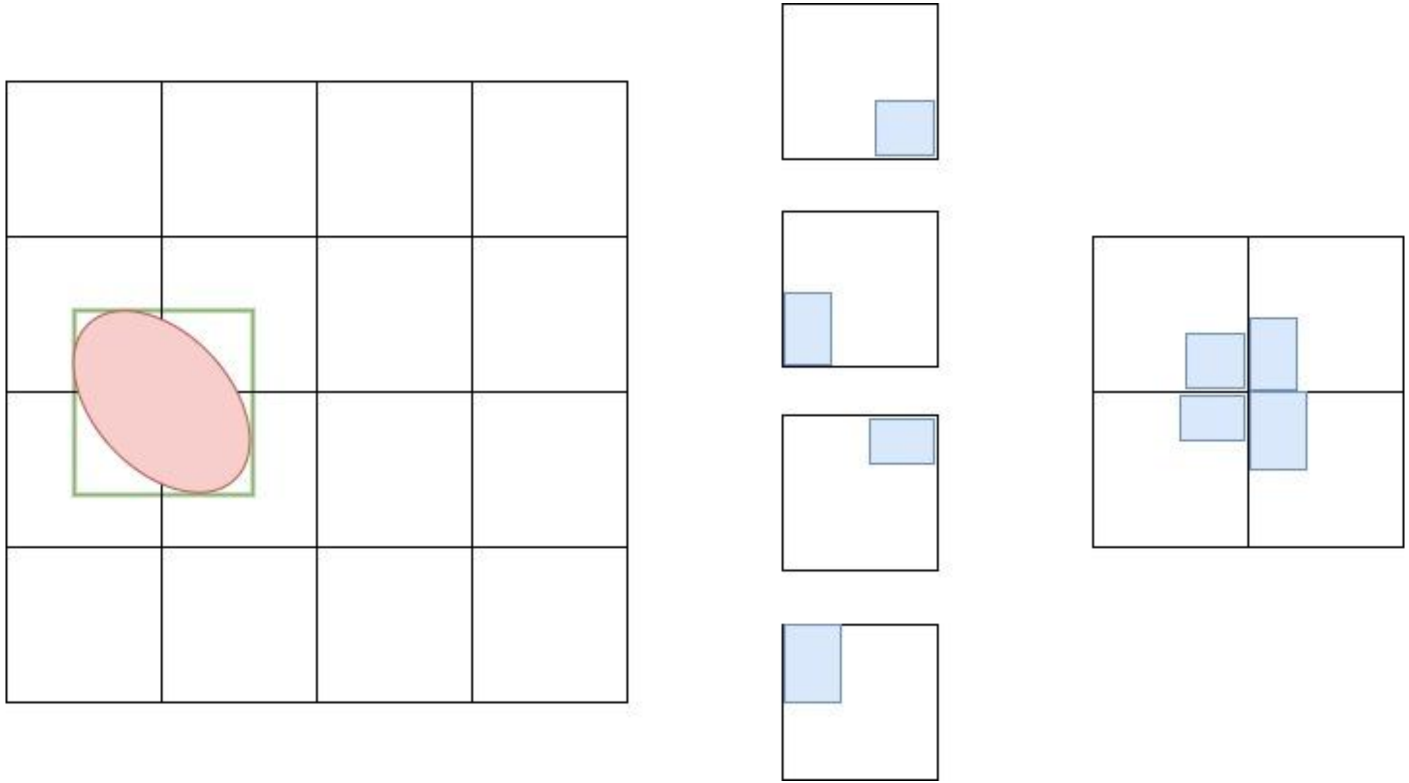
$$L(x, c, l, g) = \frac{1}{N}(L_{conf}(x, c) + \alpha L_{loc}(x, l, g))$$

Discussion



B: Benign N: Normal

Discussion



References

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2. Li, Y. R., Chan, R. H., Shen, L., Hsu, Y. C., & Isaac Tseng, W. Y. (2016). An adaptive directional Haar framelet-based reconstruction algorithm for parallel magnetic resonance imaging. *SIAM Journal on Imaging Sciences*, *9*(2), 794-821.
3. Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016, October). Ssd: Single shot multibox detector. *European conference on computer vision* (pp. 21-37). Springer, Cham.
4. Ting, F. F., Tan, Y. J., & Sim, K. S. (2019). Convolutional neural network improvement for breast cancer classification. *Expert Systems with Applications*, 120, 103-115.

Q&A