Normal binary cross-entropy loss function for two-class classification

$$L(X,y) = \begin{cases} -\log P(Y=1|X) & \text{if } y=1\\ -\log P(Y=0|X) & \text{if } y=0 \end{cases}$$

When faces class imbalance, use weighted loss

$$L(X,y) = \begin{cases} w_p \times -\log P(Y=1|X) & \text{if } y=1\\ w_n \times -\log P(Y=0|X) & \text{if } y=0 \end{cases}$$

$$w_p = \frac{\text{num negative}}{\text{num total}}$$
 $w_n = \frac{\text{num positive}}{\text{num total}}$

Weighted Loss

or use re-sampling methods: Undersampling, Oversampling

Loss function for multi-task learning

Multi-Task
$$L(X, y_{\text{mass}}) + L(X, y_{\text{pneumonia}}) + L(X, y_{\text{edema}})$$

$$L(X, y_{\text{mass}}) = \begin{cases} -w_{\text{p,mass}} \log P(Y = 1|X) & \text{if } y = 1\\ -w_{\text{n,mass}} \log P(Y = 0|X) & \text{if } y = 0 \end{cases}$$

Medical image datasets typically have 10 thousand to 100 thousand examples.

1. Trasnfer learning: Pre-training and fine-tuning.

- 2. Data augmentation: Rotate, Flip, color noise
- 3 challenges and respective solutions

Class Imbalance

Multi-Task

Dataset Size

Weighted Loss / Resampling Multi-Label Loss Transfer Learning + Data Augmentation

3 challenges for training and testing

3 Key Challenges

Patient Overlap

Set Sampling

Ground Truth

Split by Patient

Minority class Sampling Consensus voting / more definitive test

P(+ | disease)

P(- | normal)

If a patient has the disease, what is the probability that the model predicts positive?

If a patient is normal, what is the probability that the model predicts negative?

Sensitivity

Specificity

Accuracy = Sensitivity \times prevalence + Specificity \times (1 - prevalence)

PPV = P(disease|+)

NPV = P(normal|-)

Confusion Matrix

		Model Output				
		+				
GТ	Disease	True Positive (TP)	False Negative (FN)			
	Normal	False Positive (FP)	True Negative (TN)			

		Model				
		+	•			
GT	Disease	True Positive (TP)	False Negative (FN)	\Rightarrow	$\frac{TP}{TP + FN} = \mathrm{Sen}$	sitivit
	Normal	False Positive (FP)	True Negative (TN)	\Rightarrow	$\frac{TN}{FP + TN} = \operatorname{Spe}$	ecificity
		1	1			
		$\frac{TP}{TP + FP} = PPV_{p}$	$\frac{TN}{TN + FN} = \text{NP}$	v		

MRI data is 3D. If we have n sequences, treat them as n channels.

If one image doesn't align with others, use image registration.

Best way for MRI data: rotation. Shuffle the slices will change the relationships between slices.

Segmentation: 2D approach, 3D approach

Loss function for segmentation

Soft Dice Loss

$$L(P,G) = 1 - \frac{2\sum_{i}^{n} p_{i}g_{i}}{\sum_{i}^{n} p_{i}^{2} + \sum_{i}^{n} g_{i}^{2}}$$