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

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

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

Weighted Loss

or use re-sampling methods: Undersampling, Oversampling

Loss function for multi-task learning

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

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

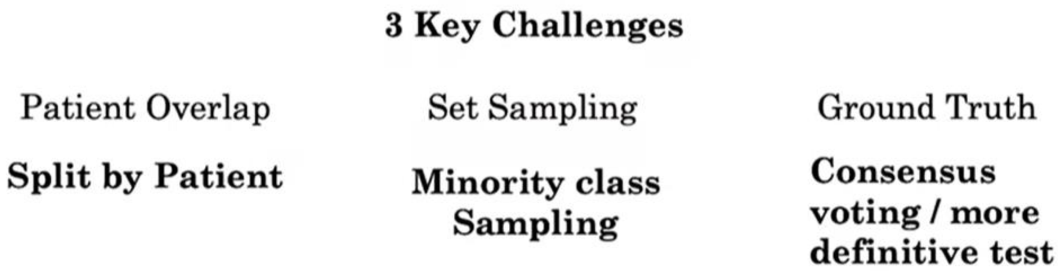
Medical image datasets typically have 10 thousand to 100 thousand examples.

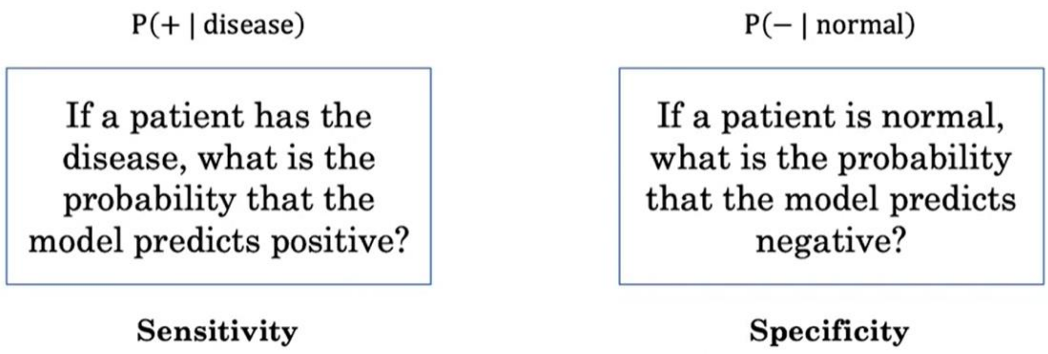
1. Trasnfer learning: Pre-training and fine-tuning.

2. Data augmentation: Rotate, Flip, color noise……

3 challenges and respective solutions

3 challenges for training and testing





$$\text{Accuracy} = \text{Sensitivity} \times \text{prevalence} + \text{Specificity} \times (1 - \text{prevalence})$$

$$PPV = P(disease|+)$$

$$NPV = P(normal|-)$$

Confusion Matrix

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

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

$$\frac{TP}{TP+FN} = \text{Sensitivity}$$

$$\frac{TN}{FP+TN} = \text{Specificity}$$

$$\frac{TP}{TP+FP} = \text{PPV}, \quad \frac{TN}{TN+FN} = \text{NPV}$$

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

$$L(P,G) = 1 - \frac{2\sum_i^n p_i g_i}{\sum_i^n p_i^2 + \sum_i^n g_i^2}$$