Predicting the probability of Polyps from CT Colonography

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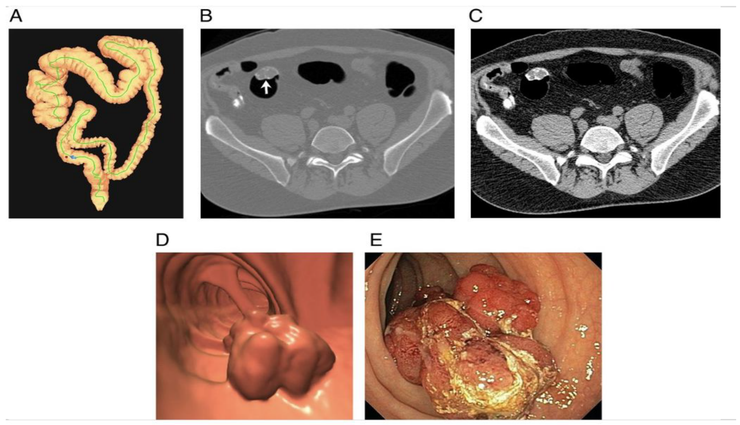
Introduction

- A computerized tomography (CT) scan is one of the most widespread imaging examination worldwide for diagnosis and screening many disorders, including adenomas, neoplasma and hemorrhages. CT colonography is used for diagnosing many conditions including neoplasia.
- The size of the polyp is used to determine whether immediate polypectomy or polyp surveillance is prefered. Polyp sizes of 6 and 10 mm are used as critical thresholds for clinical decision making.
- CT Colonography can be either prone or supine.



Dataset

3451 series and **941,771** images

115 cases which have at least one polyp above size 6mm and their histological type(836 studies).

Data input: DICOM files were inputted and concatenate to input as 3D data

Data transformation: Starting resolution 512x512, Scaling, Cubic interpolation to introduce some noise, resizing to 112x112 resolution

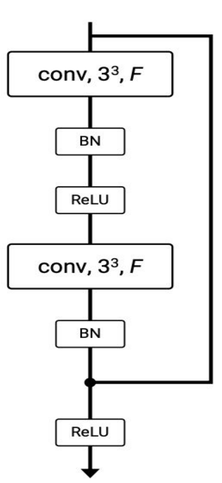
Model Architecture and Data

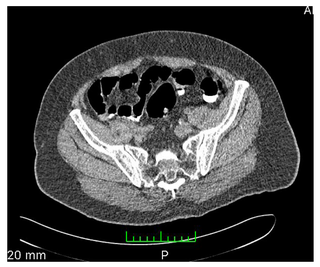
Initially we planned to do a classification to predict benign versus malignant, but the class imbalance was huge.
So we moved to classifying based on cases having a polyp versus cases that didn't and took only Supine data from each.

3D CNN model using Transfer learning using Resnet-18

3D ResNet

- A basic ResNets block consists of two convolutional layers
- Each convolutional layer is followed by batch normalization and a ReLU
- A shortcut pass connects the top of the block to the layer just before the last ReLU in the block





Layer Name	Architecture	
	18-layer	34-layer
conv1	$7 \times 7 \times 7$, 64, stride 1 (T), 2 (XY)	
conv2_x	$3 \times 3 \times 3$ max pool, stride 2 $\begin{bmatrix} 3 \times 3 \times 3, 64 \\ 3 \times 3 \times 3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3 \times 3, 64 \\ 3 \times 3 \times 3, 64 \end{bmatrix} \times 3$
conv3_x	$\begin{bmatrix} 3 \times 3 \times 3, 128 \\ 3 \times 3 \times 3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3 \times 3, 128 \\ 3 \times 3 \times 3, 128 \end{bmatrix} \times 4$
conv4_x	$\begin{bmatrix} 3 \times 3 \times 3, 256 \\ 3 \times 3 \times 3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3 \times 3, 256 \\ 3 \times 3 \times 3, 256 \end{bmatrix} \times 6$
conv5_x	$\begin{bmatrix} 3 \times 3 \times 3, 512 \\ 3 \times 3 \times 3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3 \times 3, 512 \\ 3 \times 3 \times 3, 512 \end{bmatrix} \times 3$
	average pool, 400-d fc, softmax	

Implementation

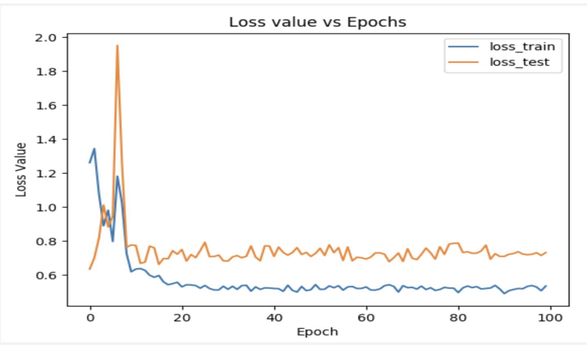
- Loss function: **NLL Loss**
- Optimization: Stochastic Gradient Descent (**SGD**) with momentum to helps accelerate gradients vectors in the right directions, thus leading to faster converging

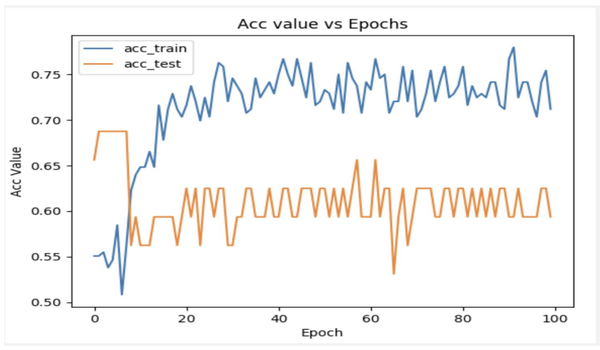
The training parameters include a weight decay of 0.001 and 0.9 for momentum

100 epochs

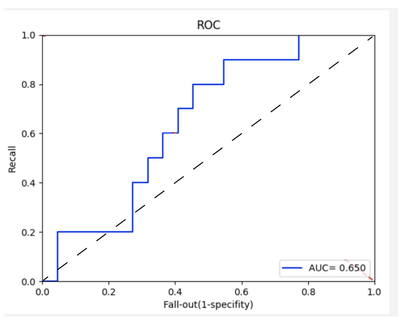
batch size of 2

Results





ROC Curve



CONCLUSION AND FUTURE WORK

- Loss function and training methodology is as important as the model architecture.
- Deep learning models can overcome biases and inference time is low.
- Future work: Experiment with other data sets and segmentation models to conclusively prove that loss scheduling is a helpful training methodology.

References

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