ELECTRICAL & COMPUTER ENGINEERING

Improved sensitivity and specificity with AI on 3D mammography

Sponsor: Mindshare Medcial
Industry Mentor: Ilya Goldberg, Michael Calhoun
Faculty Mentor: Ming-Ting Sun

Chen Bai, Drew Clark, Kyle Zhang

Problem Statement

Breast cancer is a leading cause of death in women and current methods to detect and classify lesions often result in false positives as well as failure to detect cancer. Therefore, it is desirable to find a sensitive way to detect lesions earlier, as well as to more accurately characterize lesions to reduce overdiagnosis and overtreatment. Our goal is to build neural networks to be used for localizing and characterizing breast cancer lesions in 3D digital breast tomosynthesis (DBT) scans.

To train the AI, the characterization of the lesions (benign vs. malignant) was done by pathologists using microscopy, whereas the localization (centroids) were determined by radiologists.

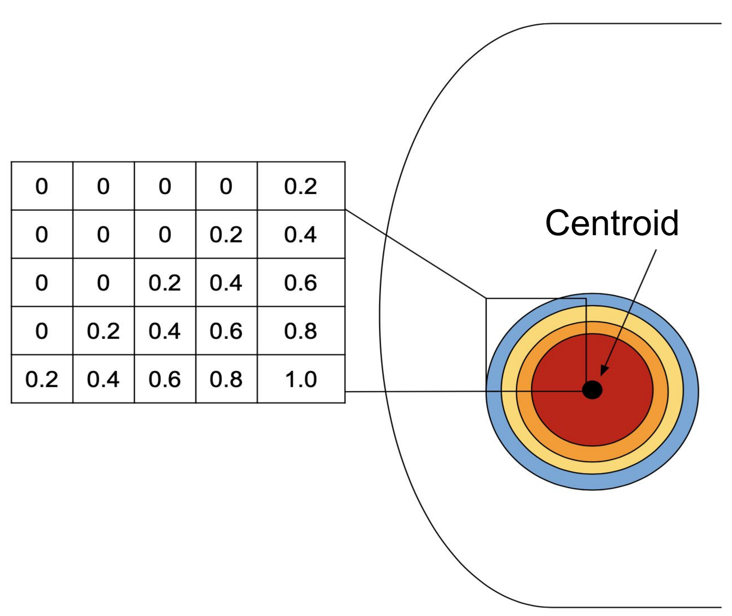
Pre-Process

- Input:
  - 3D Dicom files ("psuedo" 3D image) - Pre-normalized pixel intensities
  - CSV file of all labels (Classification and centroid of lesions)
- Data Organization:
  - Get labels
  - Manage directories
- Normalization: Normalize the resolution of each image (spacing between voxels).
  - Normalization is meant to standardize the spacing by interpolation.
  - Normalized to 0.1 mm in x, y axes, 1 mm in z axis

Localization

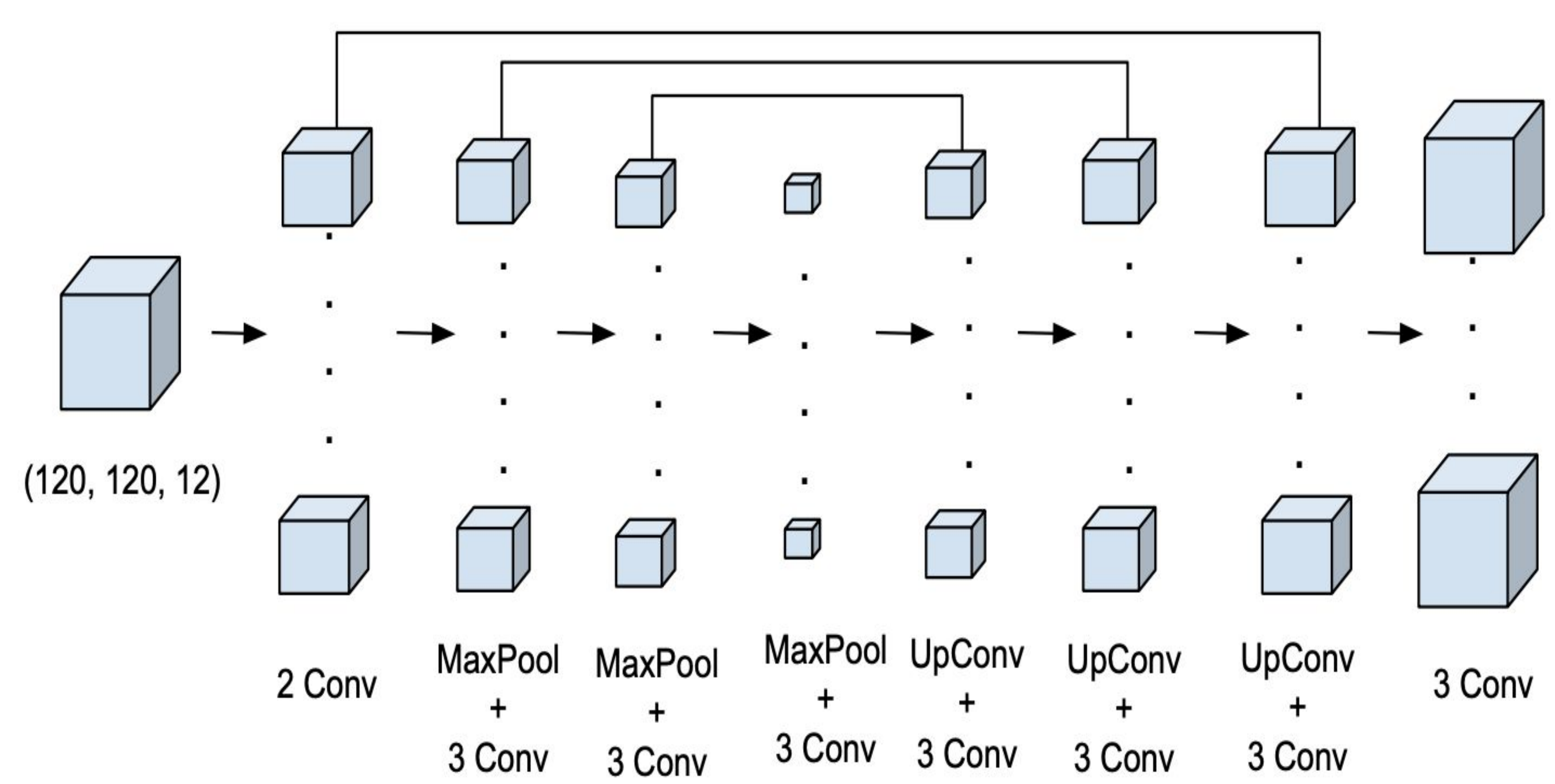
Pre-Process

- Segmentation of the normalized images using a fixed ROI (Region of Interest).
- Define label as a mask of probability as a function of the distance to centroid.
- ROI size: 120 x 120 x 12



$$f(p) = \frac{1}{e^{a\|p\|_2^2}} \text{ where } 0 < a \leq 1$$

Model



We used 3D Unet on each ROI. The first part of the model extracts features from the images. Then, it upsamples the representations and generates a mask as the probability of a lesion.

The model has 30 layers in total and has a symmetrical structure.

We also tried direct 3D CNN with downsampled data, but this requires more memory than was available.

Classification

Pre-Process

- Region of Interest (ROI)
  - 300 x 300 x 30 pixels
- Data Augmentation
  - 8x shift (Vert/Horz)
  - 3x rotate (90/180/270)
- Data splititng and organization

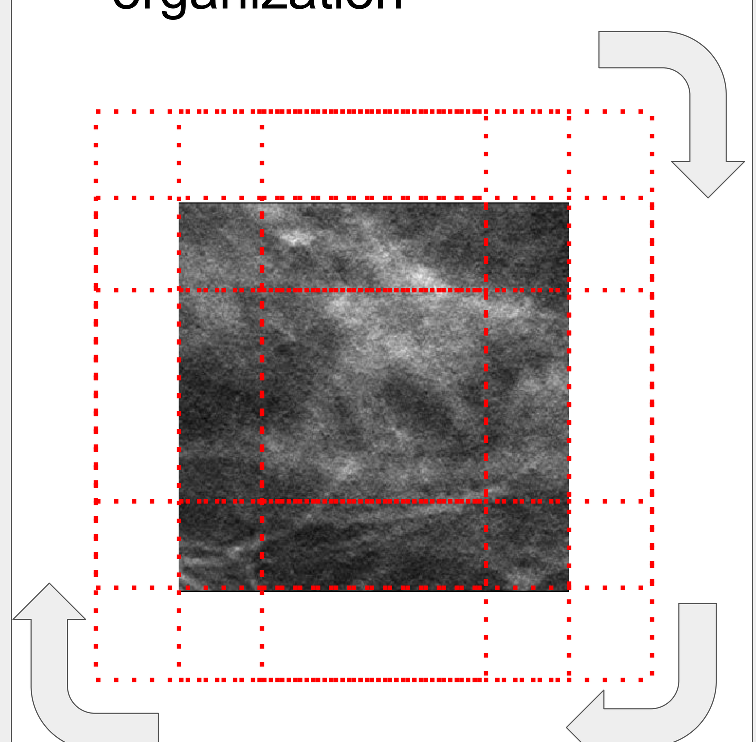
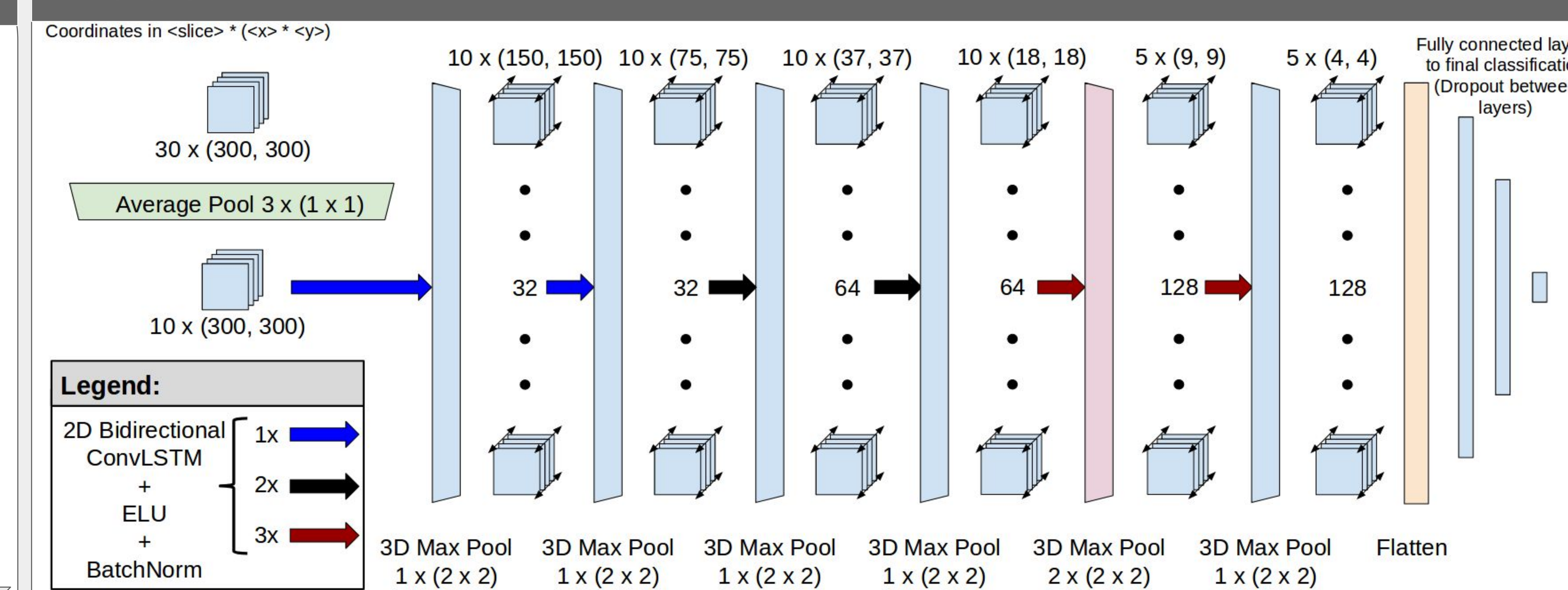


Image of one "slice" from 3D image

Model



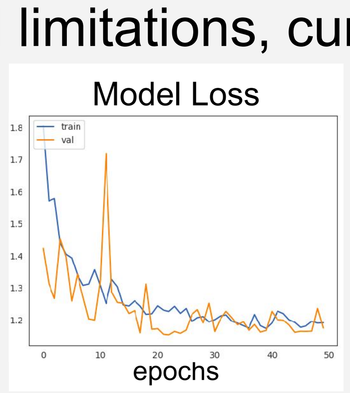
We use CNN on 2D slices, and LSTM (Long short term memory) between slices to treat z-axis like a time-series ("Scrolling through a deck of images"). The initial average pooling of the z-axis is due to very minor changes in the z-axis (alternatively skipping slices is an option). In total, there are 12 ConvLSTM, 6 Maxpool and 3 Linear layers.

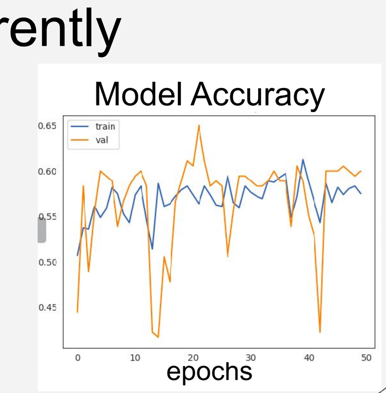
Model Details

- Optimizer: Adam
- Activation Functions:
  - ELU (exponential linear unit) for convolution and linear layers
  - Softmax for final classification

Results

- Built localizer and classifier models, rejected non-workable solutions (mostly RAM limitations)
- Parameter tuning, model optimization is a work in progress…
- Localizer: Direct 3D CNN ran into RAM limitations, currently implementing 3D UNet approach
- Classifier: Random output at first, eventually learning to latch onto slight majority class. Currently implementing more data augmentation.





Discussion

- Future work / Methods to explore:
  - Combine views (Cranial-Caudal, mediolateral-oblique) of same lesion.
  - Combine models (ensemble classification)
- Lessons Learned
  - Experience with state-of-the-art models, pre-processing techniques and building models specific to a unique dataset
- Challenges Encountered
  - "Psuedo" 3D image - Curved z-axis and resolution imbalance
  - Centroid label for localizer would work better with varied lesion sizes
  - Data and sample size - Large 3D images, but low sample count.

Acknowledgements/ References

- Ilya Goldberg - Mindshare Medical CTO
- John Callegari - Mindshare Medical Data Scientist
- Michael Calhoun - Mindshare Medical CEO
- Professor Ming-Ting Sun - Faculty Mentor

- https://github.com/juliandewit/kaggle_ndsb2017
- Cheng, Dann. Manhua, Liu. "Combining Convolutional and Recurrent Neural Networks for Alzheimer's Disease Diagnosis using PET images"