Breast Cancer Detection Assistance Model

Joe Mercer, Craig Fleischman, Jon Hilton, Alex Dauenhauer

Project Overview

- Objective: Creating a breast cancer detection model using deep learning, with the goal of increasing the detection rate of breast cancer
- Three separate models using CNN based architectures are evaluated
- Binary pathology classification of the image (labels = [benign, malignant])
- “Best” model is optimized for real-time inference using TensorRT package and deployed to edge device (Jetson TX2) for POC

Why is this Project Important?

- One in every eight women is diagnosed with invasive breast cancer in their lifetime
- The number of images per exam has increased 8x[1]
- Total number of exams increased[1]
- Number of radiologists has not kept up with the image data explosion

Project Goals

1. Create a tool that can assist radiologists with for biopsy and CT analysis
2. Improve accuracy and speed of cancer diagnosis
3. Provide radiologists with confidence levels of diagnosis so more attention and time can be focused on ambiguous samples
4. Model must be lightweight and deployable to edge devices that can live at the origin
5. PII & PHI data remain in the local office on the edge device

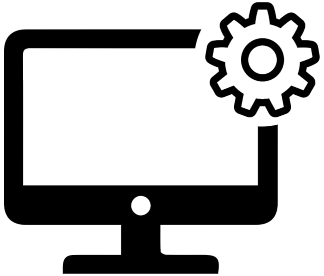
Project Pipeline

Open Source DB

Extract data from open source DBs utilizing REST APIs

COS Bucket

Leverage COS SDK to move data to and from COS bucket for resilient storage



Train Model in Cloud VM

Train model in cloud VM using GPU acceleration and optimize model for edge deployment using TensorRT.

Deploy to Edge Device

Deploy optimized model to edge device (Jetson TX2), use edge device for real-time inference

System Architecture

VM1 - transfer learning

- Ubuntu 18.04
- 16 core CPU
- 64 GB RAM
- 2TB HDD

VM2 - training from scratch

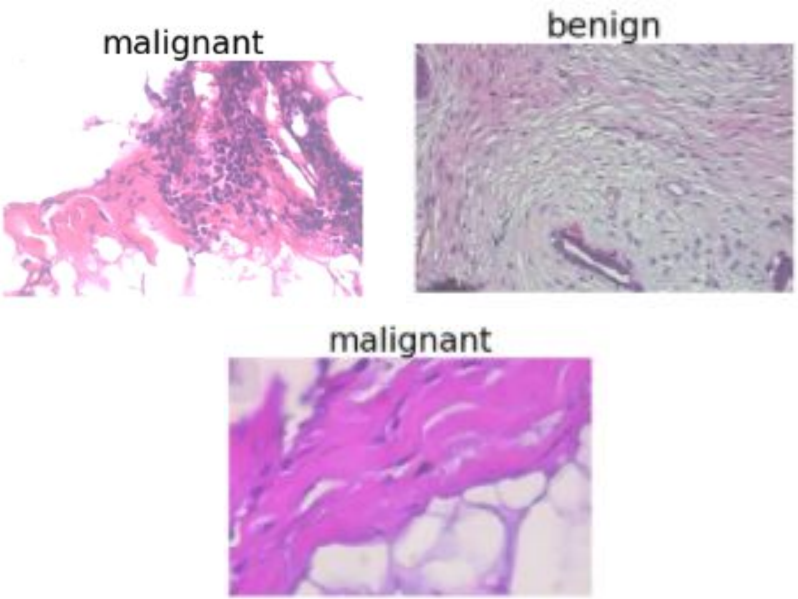
- Ubuntu 18.04
- 16 core CPU
- 2 x V100 GPU
- 120 GB RAM
- CUDA 10.0, Tensorflow 2.0 (Docker container with Python 3, Jupyter NB, TF 2.0)

Jetson TX2

- Ubuntu 16.04
- 256 core GPU
- 8 GB RAM
- 32 GB HDD

Data

- Two open source datasets were utilized:
    - The CBIS-DDSM study from The Cancer Imaging Archive (TCIA)
    - The Breast Cancer Histopathological Image Classification (BreakHis)
- The TCIA images are provided in DICOM format
    - 3,219 total images - 1,820 benign, 1,399 malignant
- BreakHis images provided in PNG format
    - 7,915 total images - 2,483 benign, 5,432 malignant
- 11,134 images total

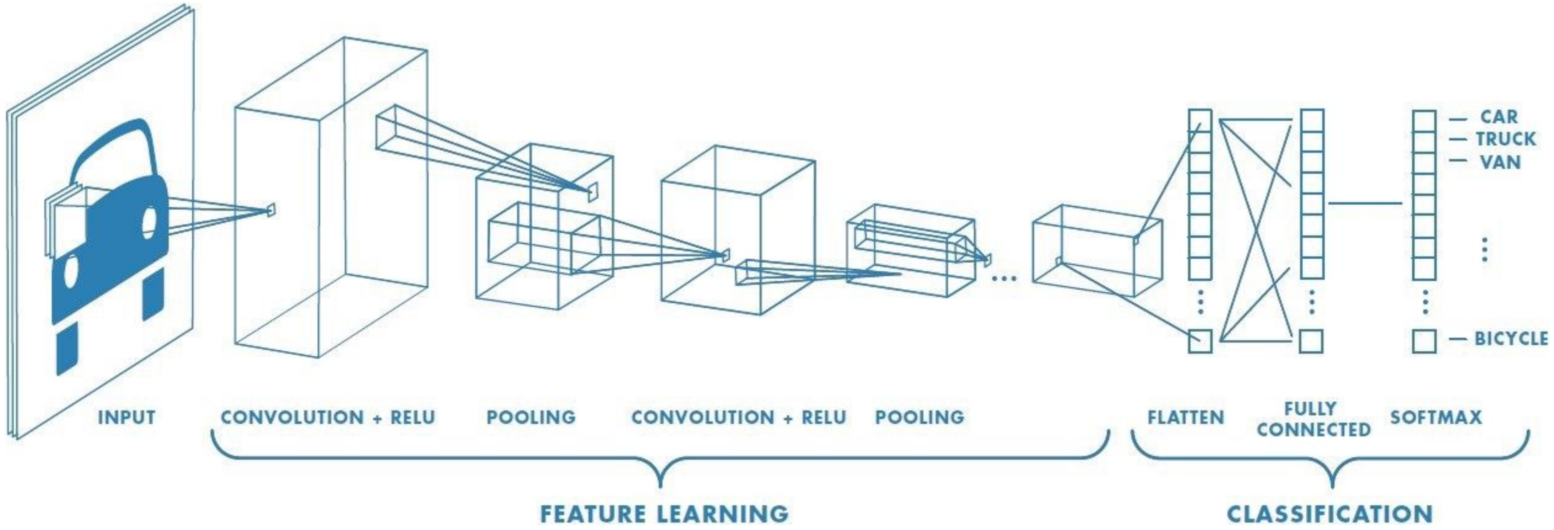


Model Development

Three separate models compared for accuracy and inference speed.

- Baseline model
  - Custom CNN architecture
  - Utilized TensorFlow 2.0 with Keras API leveraging tf.data.Datasets to manage data input
- MobileNet 224 based architecture
  - Leveraged transfer learning, re-trained only the final layer of MobileNet model on breast cancer dataset
- Resnet-152 PyTorch based architecture
  - Leveraged transfer learning from Resnet 152, re-trained final layer on dataset

Model Architecture (Baseline)



Model Architecture (MobileNet)

Retrain final layer, utilize pretrained weights for transfer learning

Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Model Architecture

(Resnet-152)

model	top-1 err.	top-5 err.
VGG-16 [40]	28.07	9.33
GoogLeNet [43]	-	9.15
PReLU-net [12]	24.27	7.38
plain-34	28.54	10.02
ResNet-34 A	25.03	7.76
ResNet-34 B	24.52	7.46
ResNet-34 C	24.19	7.40
ResNet-50	22.85	6.71
ResNet-101	21.75	6.05
ResNet-152	**21.43**	**5.71**

Resnet-152 was selected as pre-trained model due to its performance relative to other models.

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

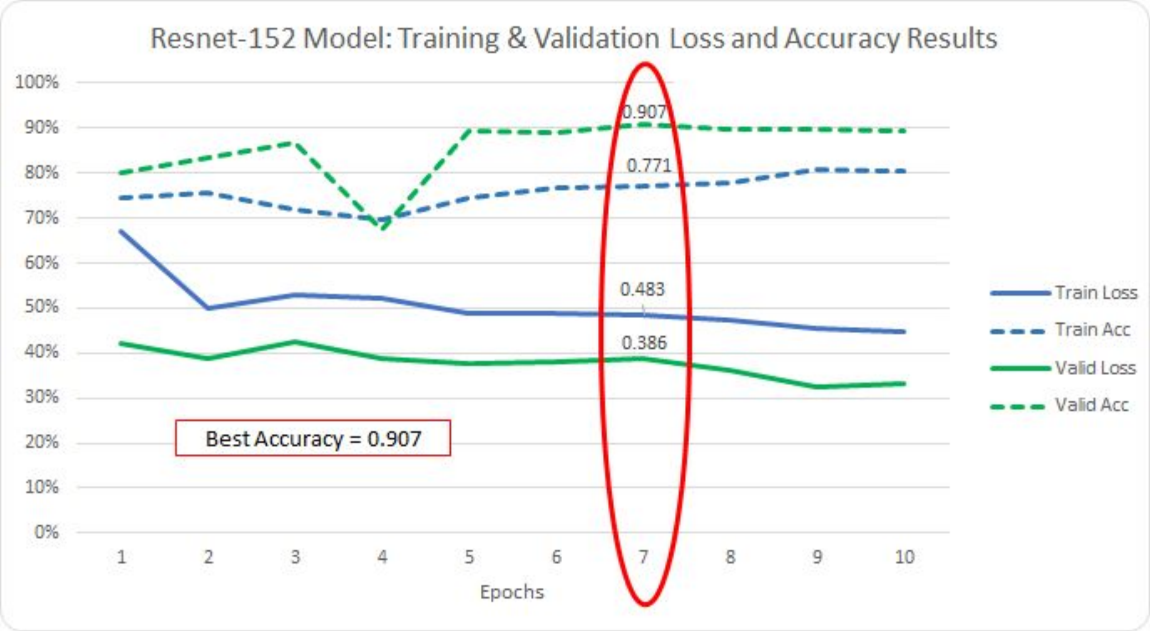
Resnet-152 architecture

+

```
classifier = nn.Sequential(OrderedDict([
                    ('fc1', nn.Linear(2048, 512)),
                    ('relu', nn.ReLU()),
                    ('dropout1', nn.Dropout(p=0.5)),
                    ('fc2', nn.Linear(512, 2)),
                    ('output', nn.LogSoftmax(dim=1))
                    ]))
```

A new untrained feed-forward classifier, using ReLU activations was added.

Model Results

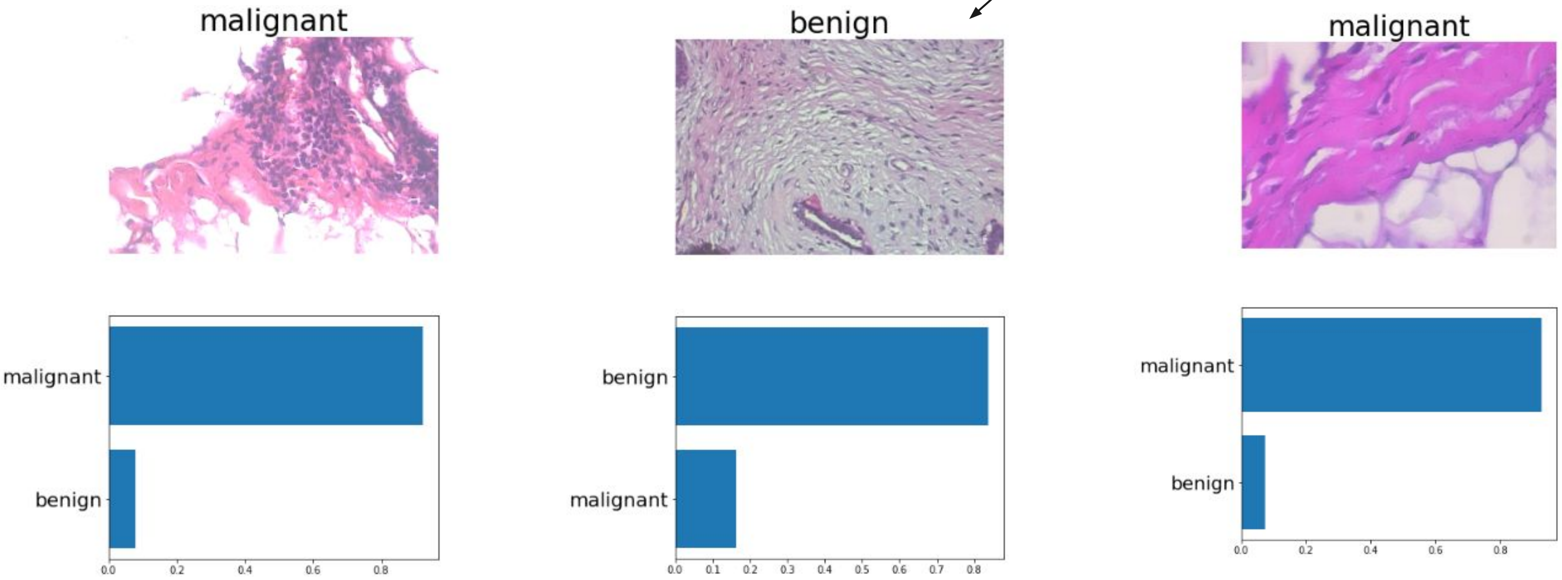


Evaluation

Model	Validation Loss	Validation Accuracy	Inference Time (sec)
Baseline CNN	0.888	0.842	0.031
MobileNet-224	0.921	0.765	0.065
Resnet-152	0.386	0.907	0.042

Sample Deployment

Radiologists can focus more time and attention on low confidence samples



Challenges & Next Steps

- Project: There were 2 different types of image datasets consumed -- from what we could tell this did not boost the learning of the models.
- Next: Visually highlight the area detected as cancer
- Next: Correctly identify the type of cancer

Thank you.

References

- **The Cancer Imaging Archive** - https://www.cancerimagingarchive.net/
- Rebecca Sawyer Lee, Francisco Gimenez, Assaf Hoogi, Kanae Kawai Miyake, Mia Gorovoy & Daniel L. Rubin. (2017) **A curated mammography data set for use in computer-aided detection and diagnosis research**. Scientific Data volume 4, Article number: 170177 DOI: 10.1038/sdata.2017.177
- **Breast Cancer Histopathological Image Classification: A Deep Learning Approach** (https://www.biorxiv.org/content/biorxiv/early/2018/01/04/242818.full.pdf)
- **Breast density classification with deep convolutional neural networks** Nan Wu, Krzysztof J. Geras, Yiqiu Shen, Jingyi Su, S. Gene Kim, Eric Kim, Stacey Wolfson, Linda Moy, Kyunghyun Cho, *ICASSP, 2018*
- https://appliedradiology.com/articles/the-radiologist-s-gerbil-wheel-interpreting-images-every-3-4-seconds-eight-hours-a-day-at-mayo-clinic
- Clark K, Vendt B, Smith K, Freymann J, Kirby J, Koppel P, Moore S, Phillips S, Maffitt D, Pringle M, Tarbox L, Prior F. The Cancer Imaging Archive (TCIA): **Maintaining and Operating a Public Information Repository, Journal of Digital Imaging**, Volume 26, Number 6, December, 2013, pp 1045-1057. DOI: 10.1007/s10278-013-9622-7
- Rebecca Sawyer Lee, Francisco Gimenez, Assaf Hoogi , Daniel Rubin (2016). **Curated Breast Imaging Subset of DDSM [Dataset]**. The Cancer Imaging Archive. DOI: 10.7937/K9/TCIA.2016.7O02S9CY
- https://blog.azumo.co/tensorflow-breast-cancer-detection-using-convolutional-neural-networks-afe083135925
- Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam, **Mobilenets: Efficient convolutional neural networks for mobile vision applications**, 2017
- https://www.nationalbreastcancer.org/breast-cancer-facts
- RESNET-152 Details: https://towardsdatascience.com/review-resnet-winner-of-ilsvrc-2015-image-classification-localization-detection-e39402bfa5d8
- https://towardsdatascience.com/building-a-convolutional-neural-network-cnn-in-keras-329fbbadc5f5
- https://towardsdatascience.com/the-4-convolutional-neural-network-models-that-can-classify-your-fashion-images-9fe7f3e5399d
- [1]https://appliedradiology.com/articles/the-radiologist-s-gerbil-wheel-interpreting-images-every-3-4-seconds-eight-hours-a-day-at-mayo-clinic