Diagnosing Lipohypertrophy at the Bedside

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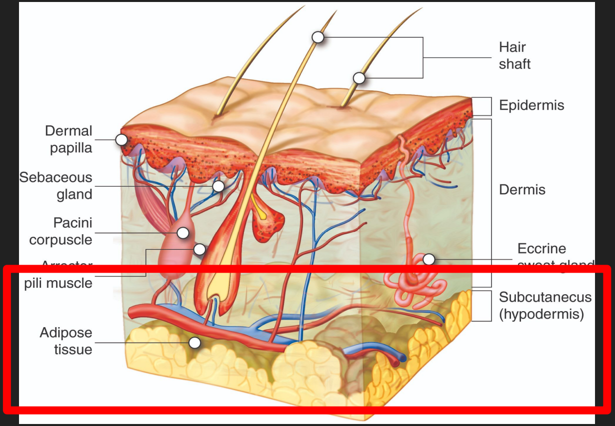
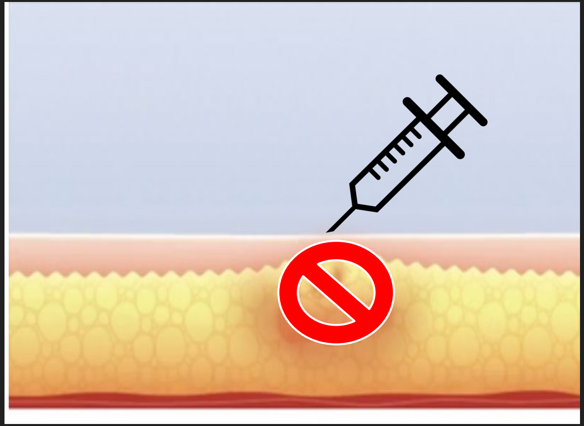
Capstone Partner – Dr. Ken Madden, Gerontology and Diabetes Research Laboratory (GDRL)

What is lipohypertrophy?

- Lipohypertrophy is a common complication for diabetic patients who inject insulin



Occurs in the deepest layer of the skin



Classified as the development of fat cells, fibrous tissue and decreased veins at injection site

Patients are unable to manage blood sugar levels

May need more insulin

Image source: 1) Lumen, 2) BD, 3) Clker

Capstone Partner's Needs

- Research has suggested that ultrasound imaging is much more effective than physical examination of the body
- The criteria used to classify is currently implemented by a small group of physicians only

Can we leverage supervised machine learning techniques to accurately classify the existence of lipohypertrophy given an ultrasound image?

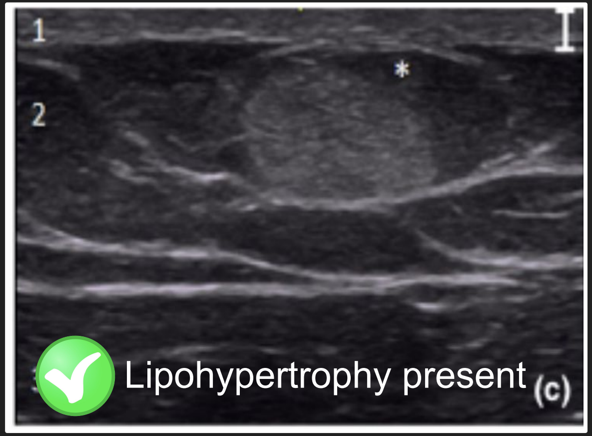


Image source: 1) Kapeluto et al.(2018), 2) From Dataset 3) Clker

Data Provided

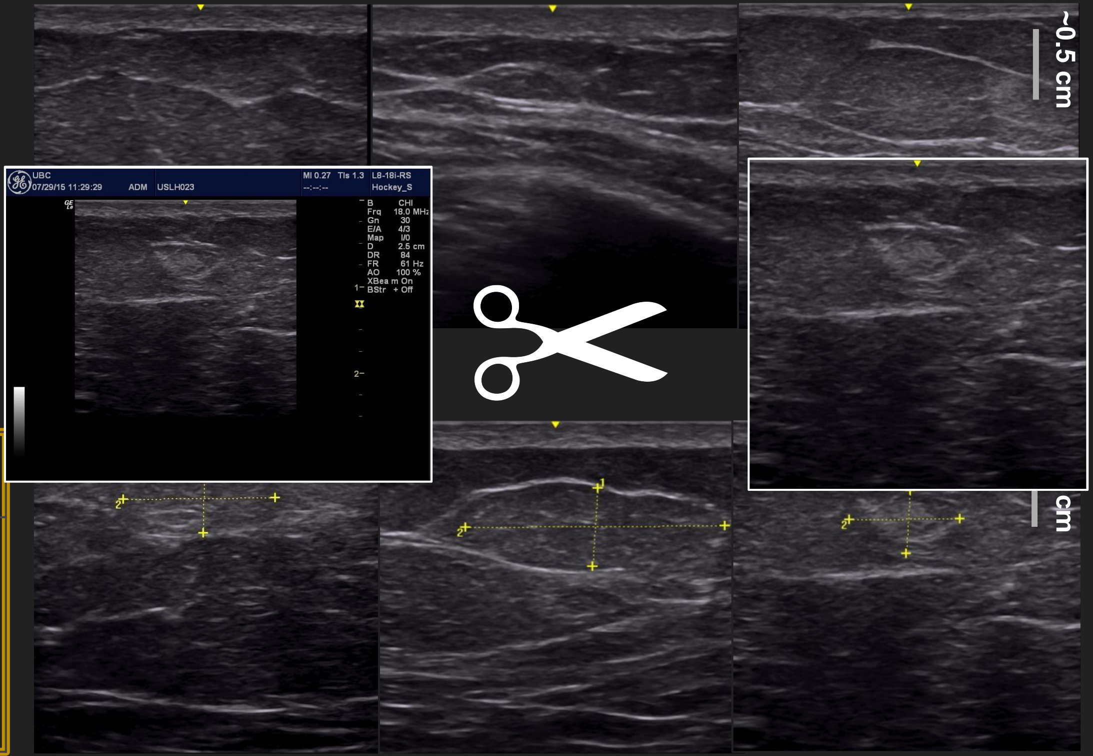
Negative - lipohypertrophy is **not present**

Positive - lipohypertrophy is **present**

Pre-processing steps were required

	Positive	Negative
Count	**135**	**218**
Proportion	**38%**	**62%**

Negative Examples:



Our Data Science Objectives

- To develop a image classification CNN model that will classify ultrasound images with high accuracy
- To deploy the model for a non-technical audience using an easy-to-use interface

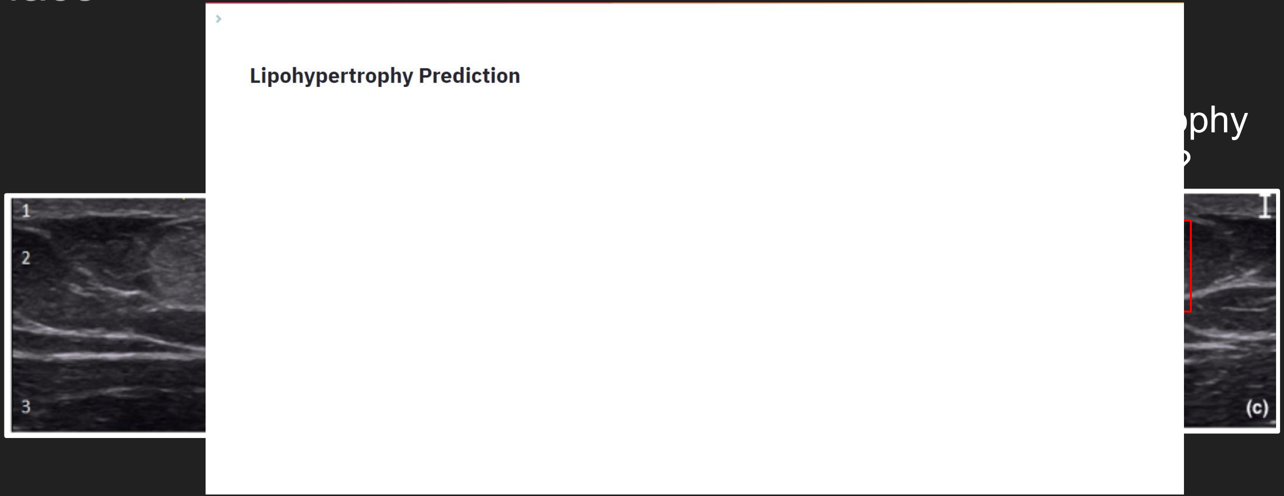


Image source: 1) [Kapeluto et al.(2018).]()

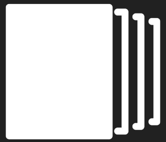
Target Audience

- Primary Audience: Healthcare professionals
  - Unfamiliar with Programming

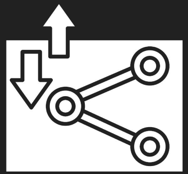
- Secondary Audience: Researchers and Ultrasound Manufacturers
  - Proof of Concept

Image source: 1) Peninsula

Data Science Techniques

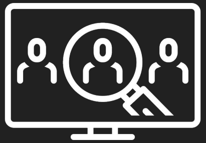


Data Augmentation

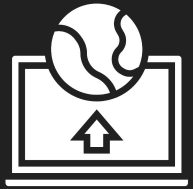


Transfer Learning

Optimization



Object Detection

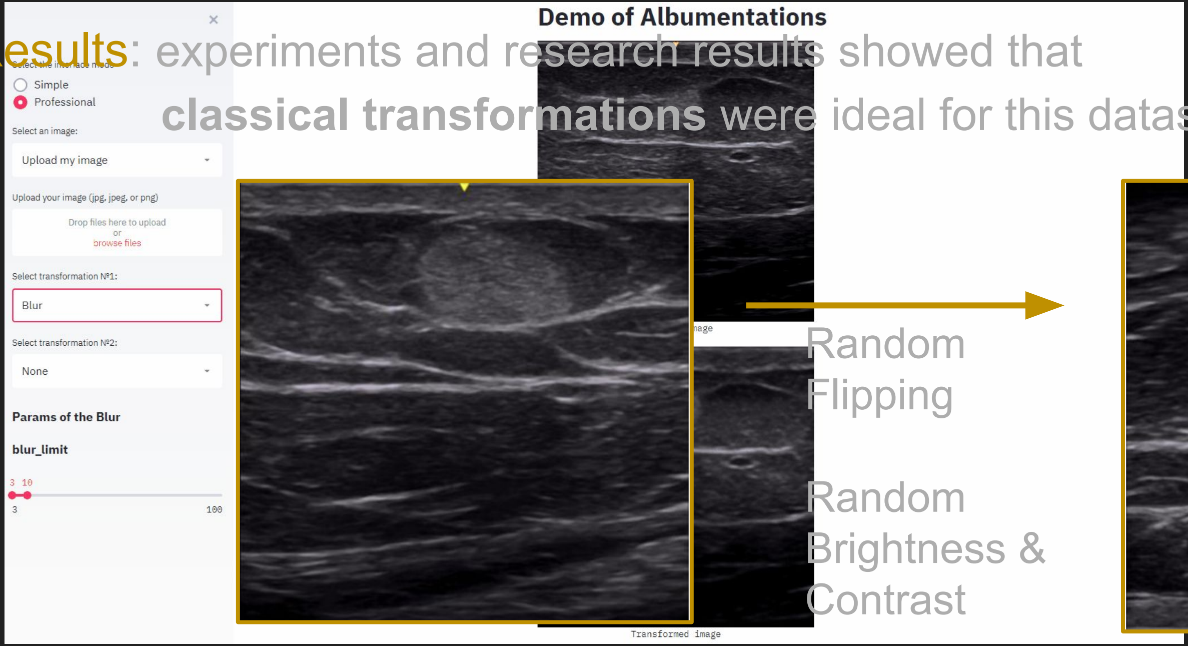


Deployment

Image source: 1) allex 2) Nunung Perdana 3) Eucalyp 4) priyanka 5) mynamepong

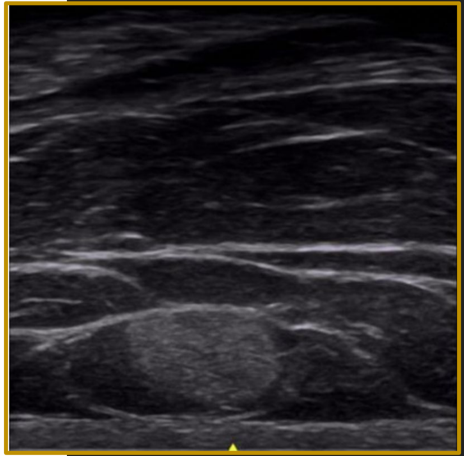
Data Augmentation

- Approach
  - Classical transformations
  - Machine learning tool approach
- Results: experiments and research results showed that **classical transformations** were ideal for this dataset



Random Flipping

Random Brightness & Contrast



Various Transfer Learning Architectures

	Test Accuracy	Test Recall	Size (MB)
DenseNet	0.76	0.76	31
Inception	0.74	0.52	101
VGG	0.65	0.19	537
ResNet	0.61	0.00	99

Architectural Changes

Reducing the Generalizable Error

Dropout Layers

- Help **prevent overfitting** BUT reduces overall accuracy
- Hyperparameter: Dropout Rate

Batch Normalization

- Reduces the number of epochs required to train ➡ **improves efficiency**

Ensemble Approach

- Similar model performances
- Computationally expensive

Architectural Changes

Optimizing Recall

- Purpose
  - In clinical setting, focus on maximizing the classification of **positive** examples
  - If mass is **present**, it is crucial to **detect** it

- Approach
  - Adjusting pos_weight in Loss function
  - Heavier penalization of misclassified true positives

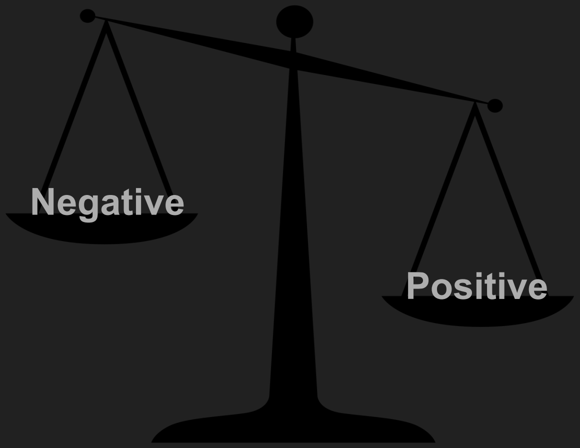
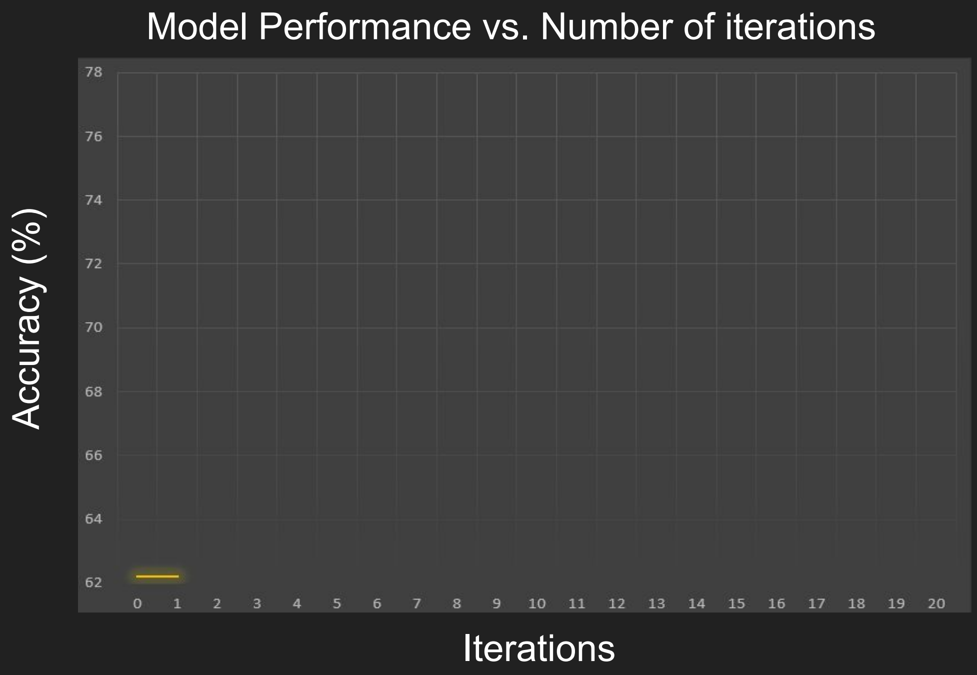


Image source: 1) ClipArtMax

More Optimization Techniques!

Using Bayesian Optimization

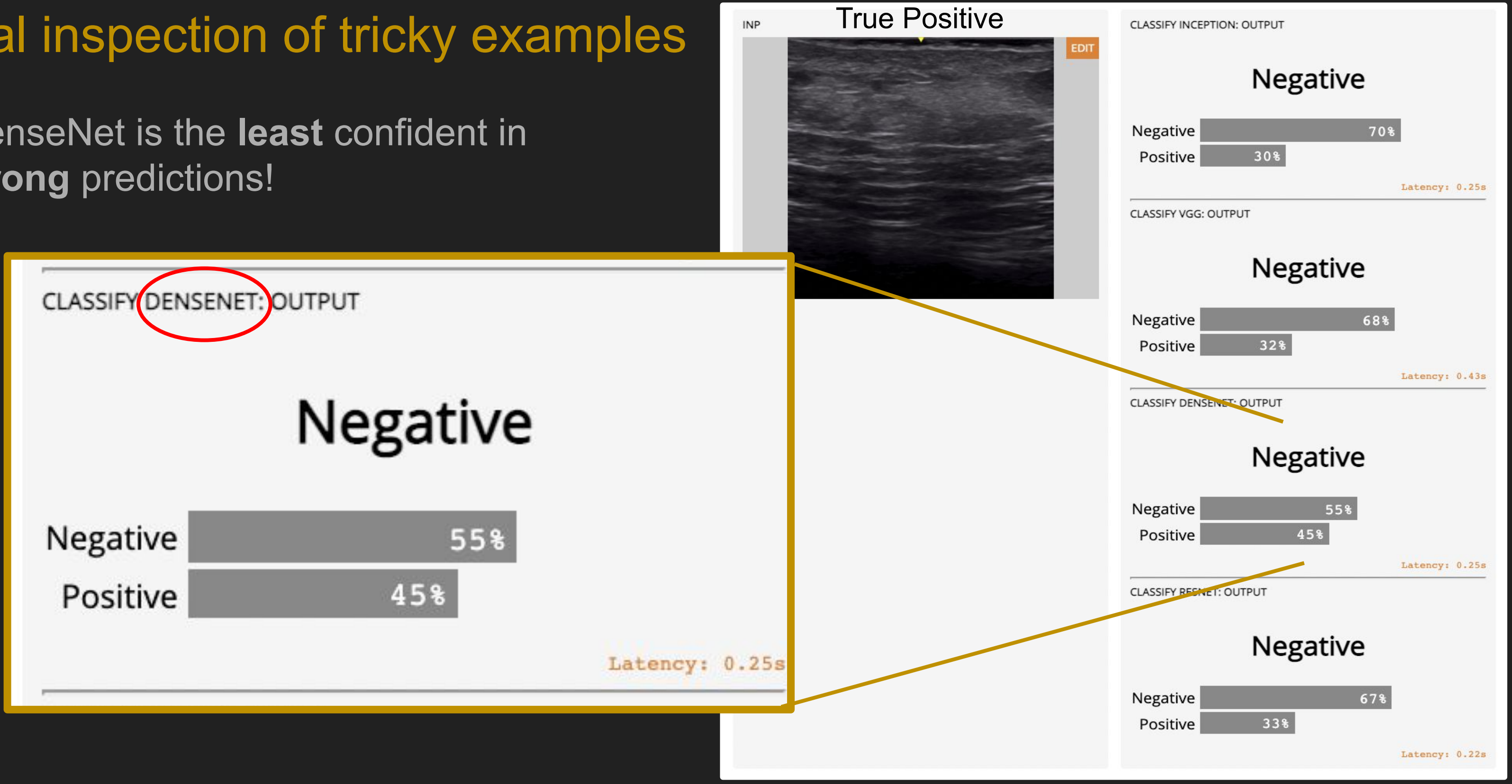
- Purpose:
  - **optimize** the learning rate and beta **hyperparameters**
- Tools:
  - **Ax** by Facebook
  - BoTorch



Final Model Selection

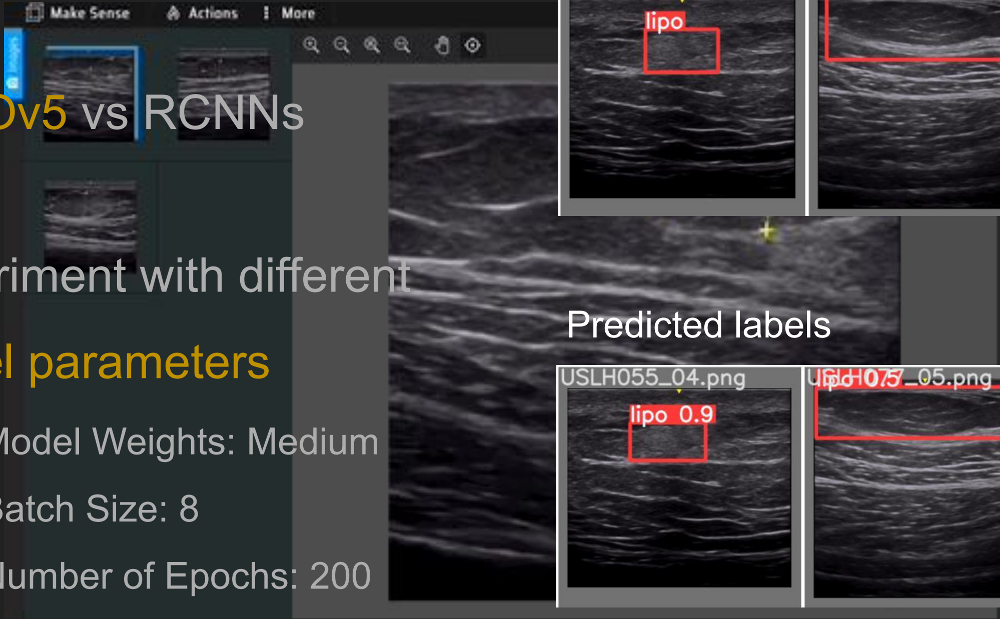
Manual inspection of tricky examples

- DenseNet is the **least** confident in **wrong** predictions!

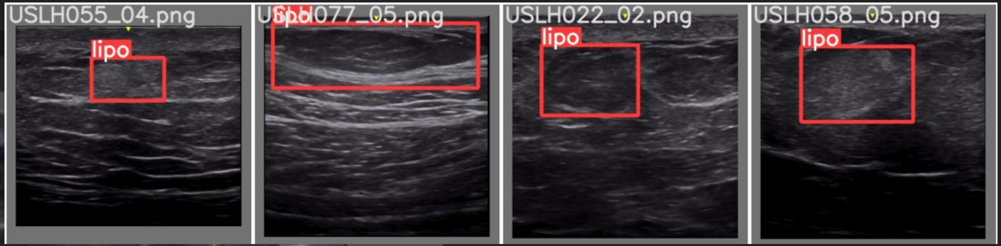


Object Detection

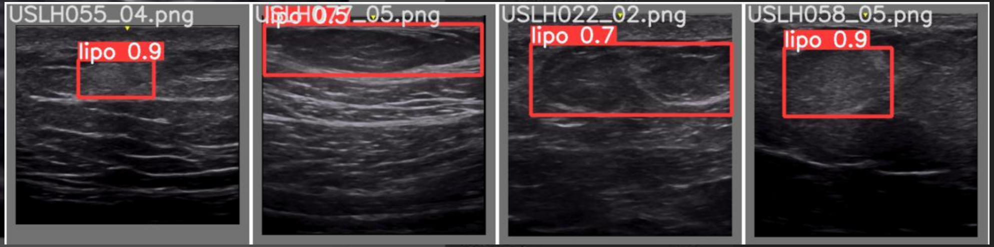
- Create bounding boxes
- YOLOv5 vs RCNNs
- Experiment with different model parameters
    - Model Weights: Medium
    - Batch Size: 8
    - Number of Epochs: 200



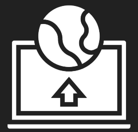
True labels



Predicted labels



Deployment



Local

Pros:

- No server maintenance required

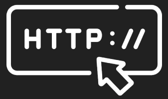
Cons:

- Multi-week IT clearance to install
- Requires significantly more time and effort to build

Online (Preferred)

Pros:

- Easier to share
- IT Clearance not required

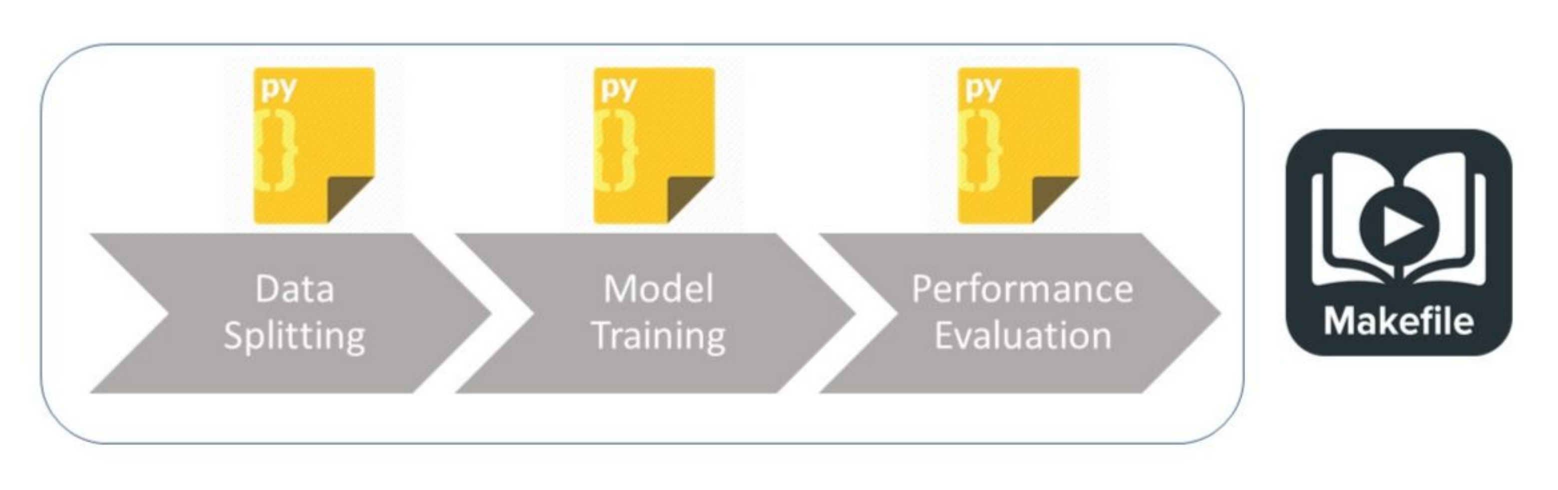


Cons:

- May require maintenance

Image source: 1) Flaticon 2) Flaticon

Data Product Showcase: Source Code



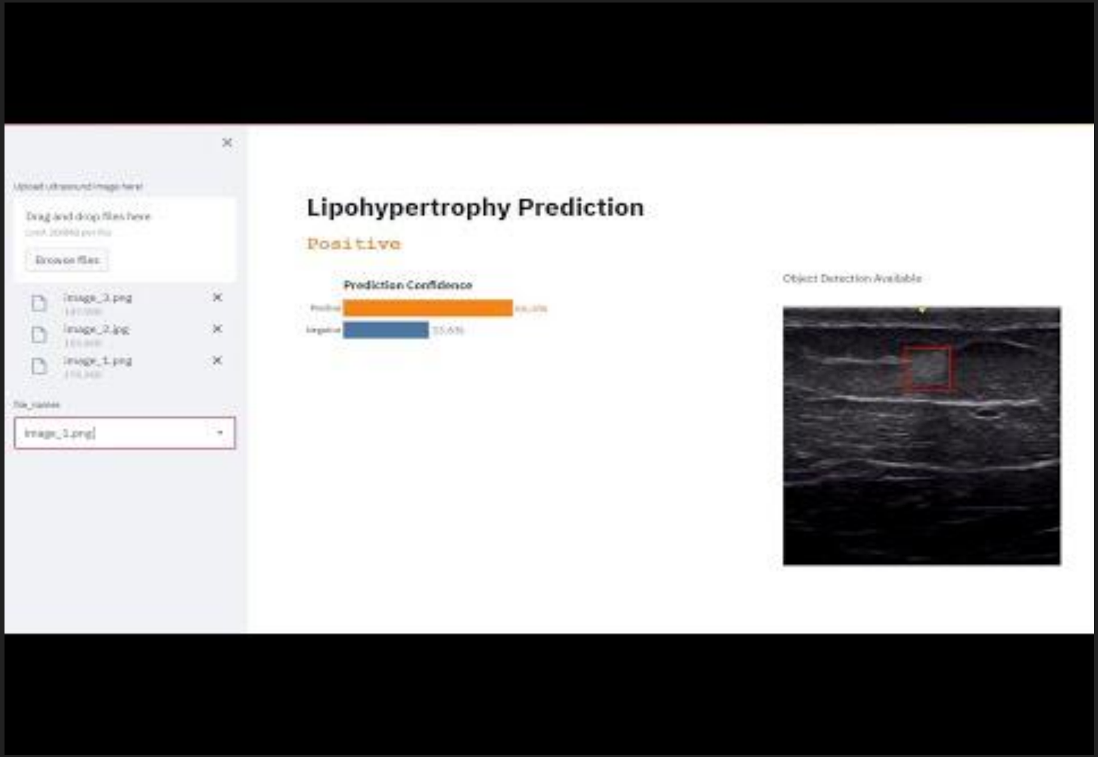
Live Demo

of

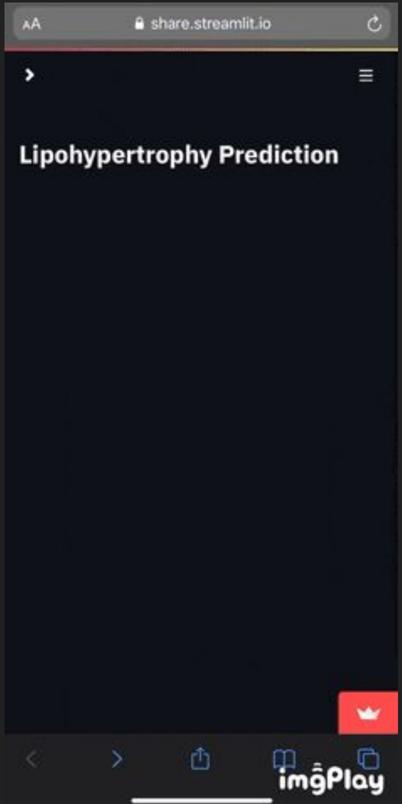
Streamlit App

Data Product Showcase: Mobile Interface

Web Interface



Smartphone Interface



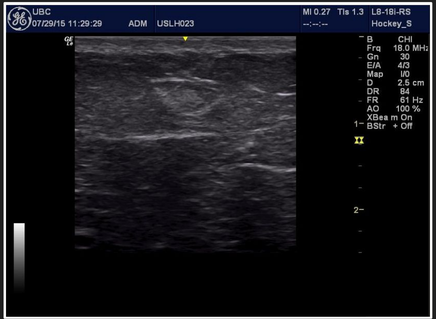
Limitations

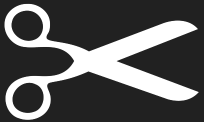
- Scarcity of data
  - Variability between experiments
  - Sensitivity to data splitting
- Limited resources
  - Inability to concurrently tune all parameters
- Lack of Oversight
  - Representation bias
  - Ongoing monitoring required

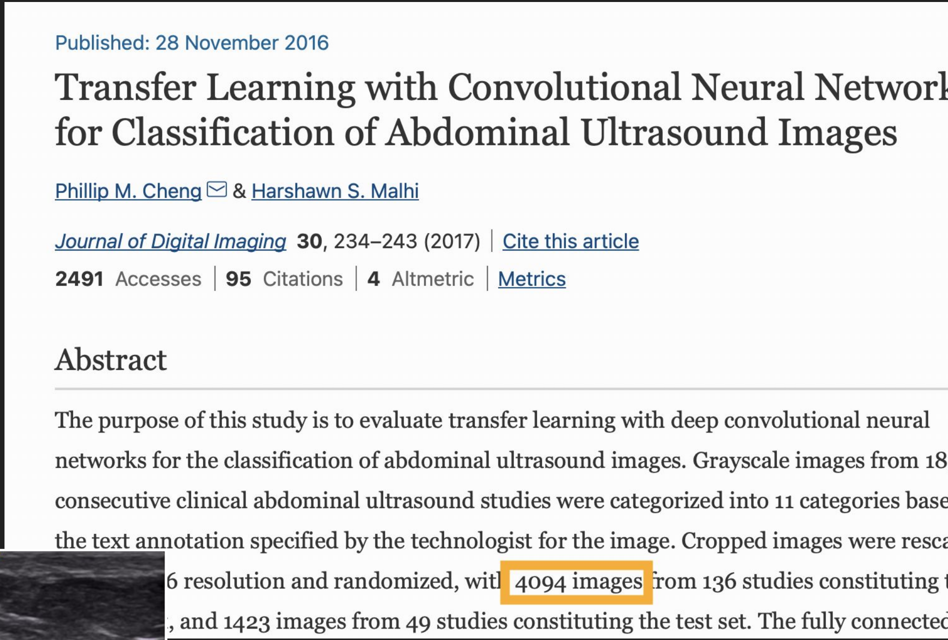
Created by ic2icon
from Noun Project

Areas for Improvement

- Expand Dataset
- Increase Computational Resources
- Add Additional Functionality






Published: 28 November 2016

Transfer Learning with Convolutional Neural Network
for Classification of Abdominal Ultrasound Images

Phillip M. Cheng & Harshawn S. Malhi

Journal of Digital Imaging **30**, 234–243 (2017) | Cite this article

2491 Accesses | **95** Citations | **4** Altmetric | Metrics

Abstract

The purpose of this study is to evaluate transfer learning with deep convolutional neural networks for the classification of abdominal ultrasound images. Grayscale images from 18
consecutive clinical abdominal ultrasound studies were categorized into 11 categories base
the text annotation specified by the technologist for the image. Cropped images were resca
6 resolution and randomized, wit 4094 images from 136 studies constituting t
, and 1423 images from 49 studies constituting the test set. The fully connected

Image source: 1) Cheng & Malhi (2016), 2,3) From Dataset

Thank you for listening!

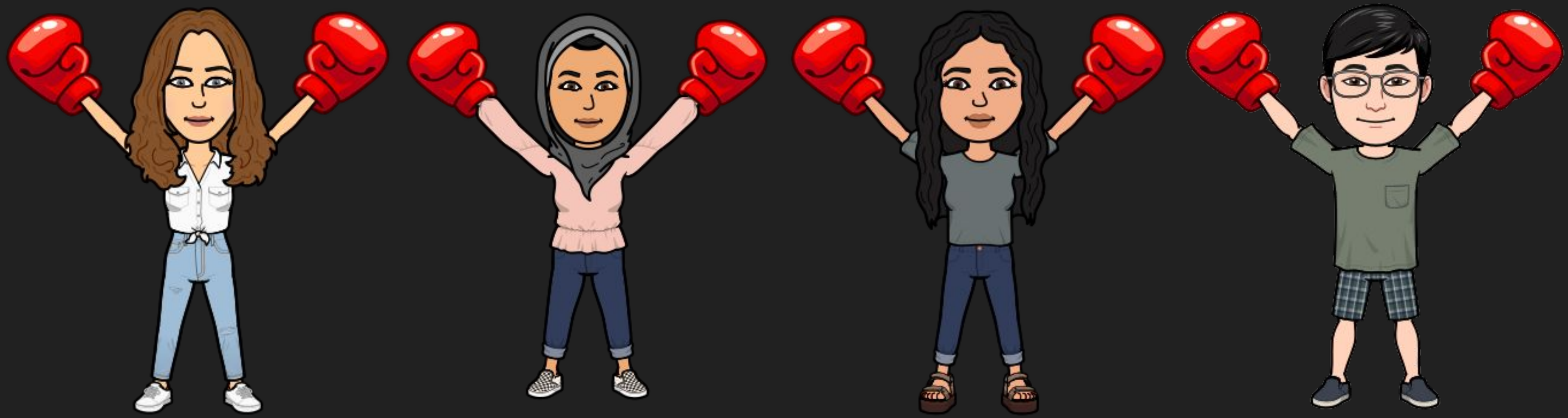


Image source: Bitmoji, MDS 572

Any questions?

Image source: [PinClipart]

Appendix Slides
in
Anticipation for Questions

Image source: NounProject

Literature Review

Classical vs. Machine Learning Augmentations

Table 3 DTL testing accuracy for the different four scenarios

From: A deep transfer learning model with classical data augmentation and CGAN to detect COVID-19 from chest CT radiography digital images

Dataset	AlexNet (%)	VGGNet16 (%)	VGGNet19 (%)	GoogleNet (%)	ResNet50 (%)
COVID-19	67.34	72.36	76.88	75.38	76.38
COVID-19 with augmentation	75.38	77.89	69.35	76.88	**82.91**
COVID-19 with CGAN	68.34	70.85	73.37	75.88	77.39
COVID-19 with aug and CGAN	76.38	78.89	73.87	77.39	81.41

Citation: Loey, Manogaran & Khalifa, 2020

Literature Review

Model Architectures and Variants

DenseNet achieving as high as 89.3% test accuracy

Diagnostic Efficiency of the Breast Ultrasound Computer-Aided Prediction Model Based on Convolutional Neural Network in Breast Cancer

Heqing Zhang, Lin Han, Ke Chen, Yulan Peng & Jiangli Lin

Journal of Digital Imaging **33**, 1218–1223 (2020) | Cite this article

Abstract

This study aimed to construct a breast ultrasound computer-aided prediction model based on the convolutional neural network (CNN) and investigate its diagnostic efficiency in breast cancer. A retrospective analysis was carried out, including 5000 breast ultrasound images (benign: 2500; malignant: 2500) as the training group. Different prediction models were constructed using CNN (based on InceptionV3, VGG16, ResNet50, and VGG19). Additionally,

Sun Q., Lin X., Zhao Y., Li L., Yan K., Liang D., Sun D. and Zhi-Cheng Li, 2020

Deep Learning vs. Radiomics for Predicting Axillary Lymph Node Metastasis of Breast Cancer Using Ultrasound Images: Don't Forget the Peritumoral Region

Qiuchang Sun[1†], Xiaona Lin[2†], Yuanshen Zhao[1], Ling Li[3], Kai Yan[1,4], Dong Liang[1], Desheng Sun[2*] and Zhi-Cheng Li[1*]

[1]Institute of Biomedical and Health Engineering, Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences, Shenzhen, China
[2]Department of Ultrasonic Imaging, Peking University Shenzhen Hospital, Shenzhen, China
[3]Ultimage Lab, Suzhou, China
[4]Peng Cheng Laboratory, Shenzhen, China

Objective: Axillary lymph node (ALN) metastasis status is important in guiding treatment in breast cancer. The aims were to assess how deep convolutional neural network (CNN) performed compared with radiomics analysis in predicting ALN metastasis using breast ultrasound, and to investigate the value of both intratumoral and peritumoral regions in ALN metastasis prediction.

Methods: We retrospectively enrolled 479 breast cancer patients with 2,395 breast ultrasound images. Based on the intratumoral, peritumoral, and combined intra- and peritumoral regions, three CNNs were built using DenseNet, and three radiomics models were built using random forest,

Zhang H., Han L., Chen K., Peng Y. & LinY. , 2020

InceptionV3, **VGG16**, **ResNet50** achieving as high as 91% test accuracy