MIA - Crowd-assisted Medical Image Annotation

Arthur Jochems Deniz Iren Amrapali Zaveri

THE D-LAB
Decision Support For Precision Medicine

BISS

Maastricht University
Institute of Data Science

Lung
Cancer

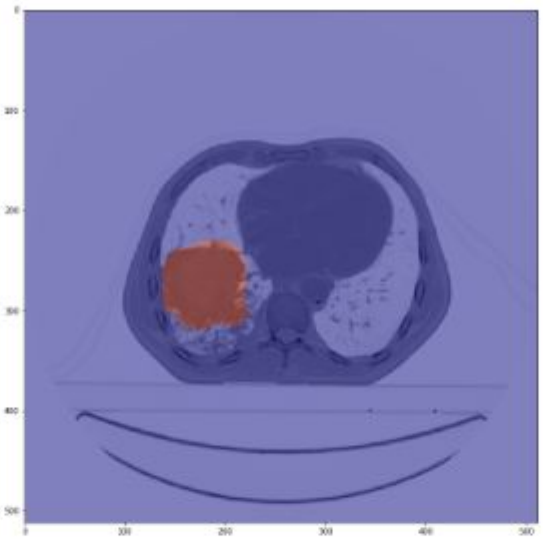
Claims
2.5 Million
lives
yearly

Problem — Personalized treatment

- For cases in which **surgery is not an option**, chemoradiotherapy is the standard treatment modality.
- However, numerous **other treatment** options exist, such as immunotherapy and a variety of systemic anti-cancer therapies.
- In order to **personalize treatment**, we <u>extract quantitative imaging features</u> from the tumor of the patient.

Problem — Annotating images

- <u>Extract quantitative imaging features</u> is done by domain experts i.e. doctors
  - Time consuming
  - Not scalable
  - Expensive
- Automated methods such as machine-learning require large amounts of input data to perform accurately
- Non-experts
  - Fast
  - Scalable
  - Inexpensive



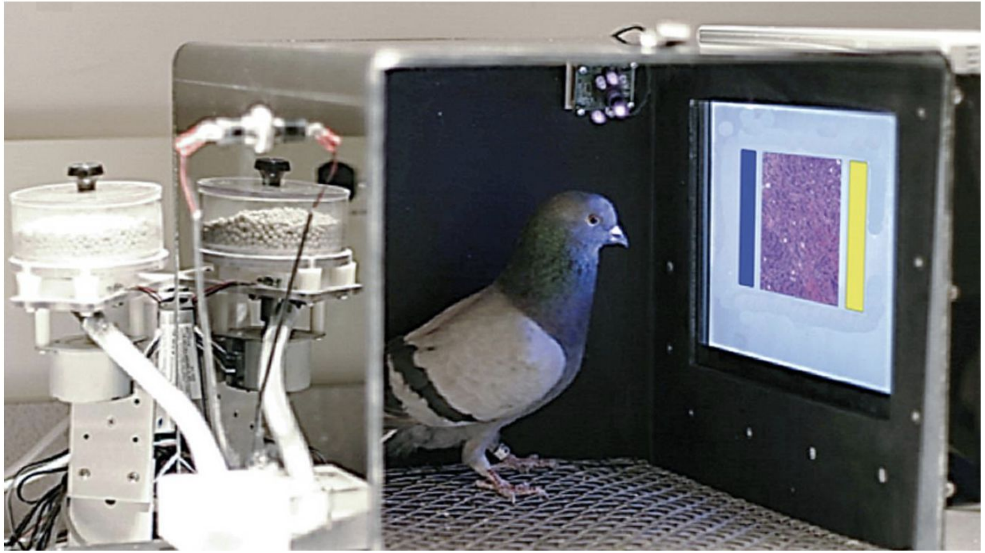
Research Question(s)

Can we use non-experts via crowdsourcing to curate open clinical imaging data?

Can we assist non-experts to carry out a mission-critical labeling task?

Related Work - Image Annotation

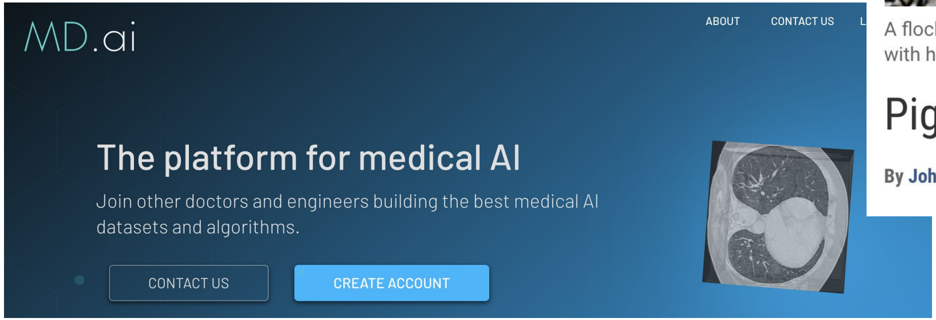
Figure 1: An example of bounding box annotations for the "bottle" category.



A flock of pigeons was able to correctly spot cancer in breast tissue biopsy images with 99% accuracy, on par with human experts. R. M. LEVENSON *ET AL.*, *PLOS ONE* (18 NOVEMBER 2015)

Pigeons spot cancer as well as human experts

By **John Bohannon** | Nov. 18, 2015 , 2:00 PM



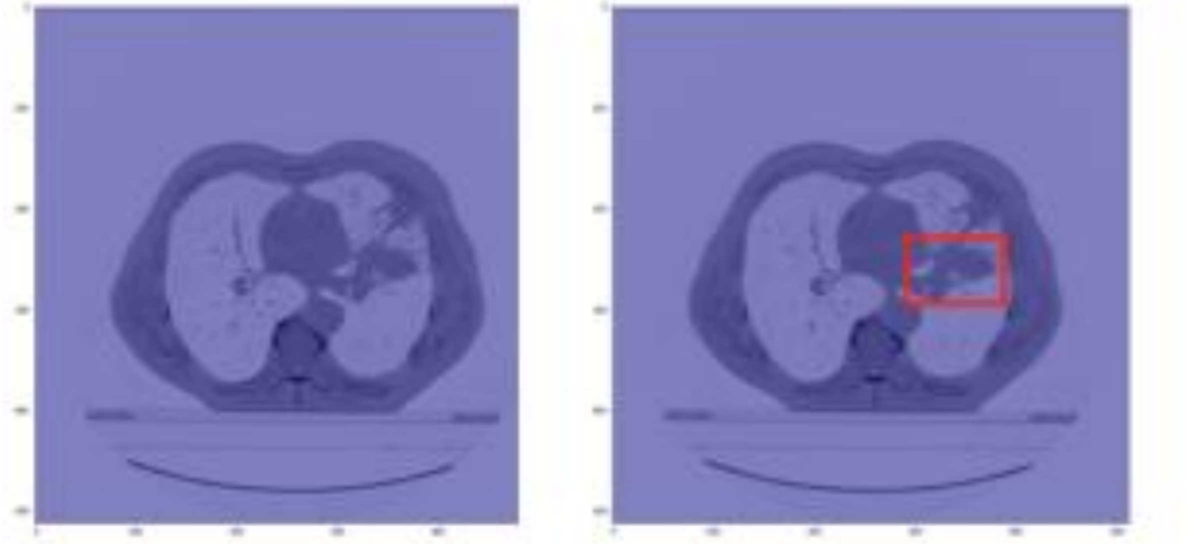
Methodology — Dataset

- **medical images of cancer**, available for public download and re-use
- data is organized as "**Collections**", typically of patients related by a common disease e.g. lung cancer
- images are available in a **DICOM** format
- **422** non-small cell lung cancer (NSCLC) patients*
  - pretreatment CT scans, manual delineation by a radiation oncologist of the 3D volume of the gross tumor volume and clinical outcome data are available
- of these 422, **360** images have been contoured by experts (doctors).
- the remaining **62** require precise contouring, which will be our dataset for the crowdsourcing experiment.

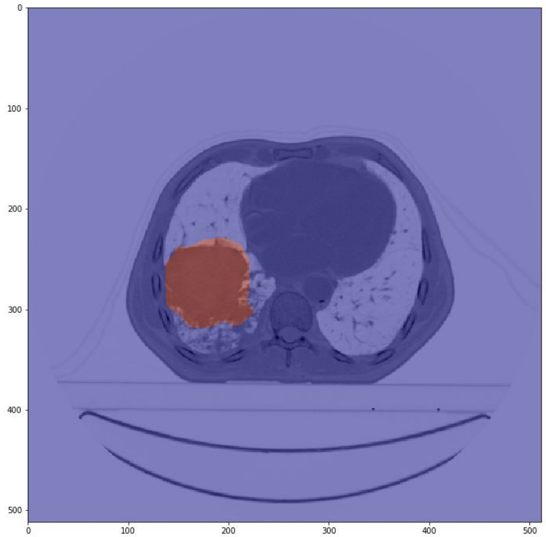
*https://wiki.cancerimagingarchive.net/display/Public/NSCLC-Radiomics

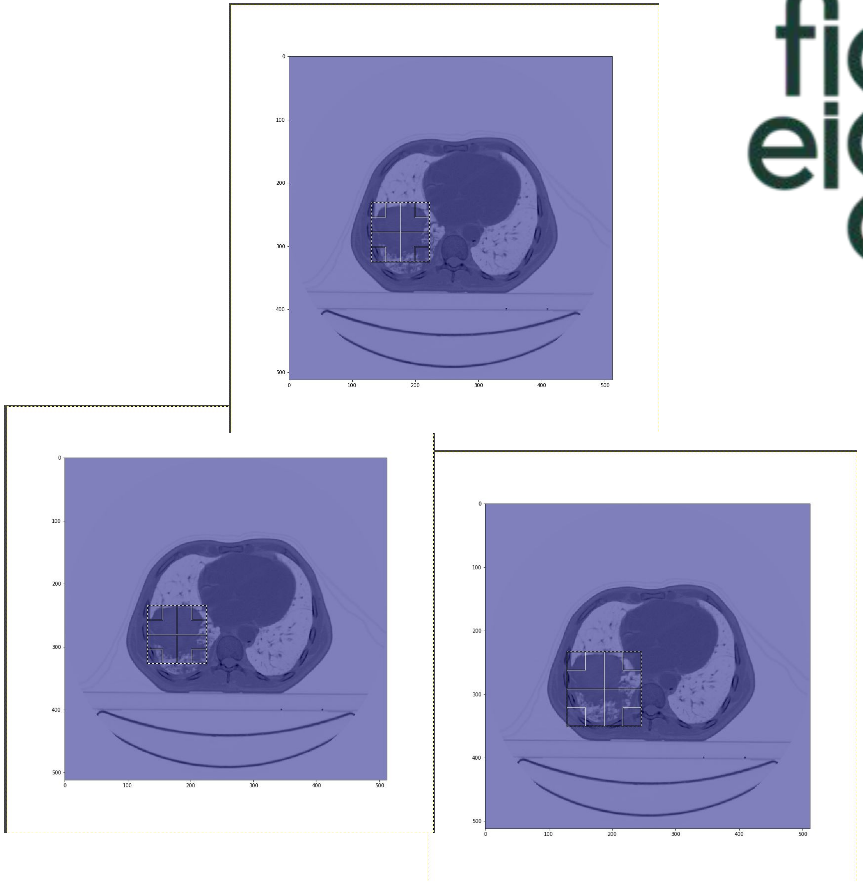
Preliminary Experiment on Figure Eight

- No. of Tasks: 15
- No. of Workers: 3 per task
- Task Design: bounding box
- Payment: 5 cents/task

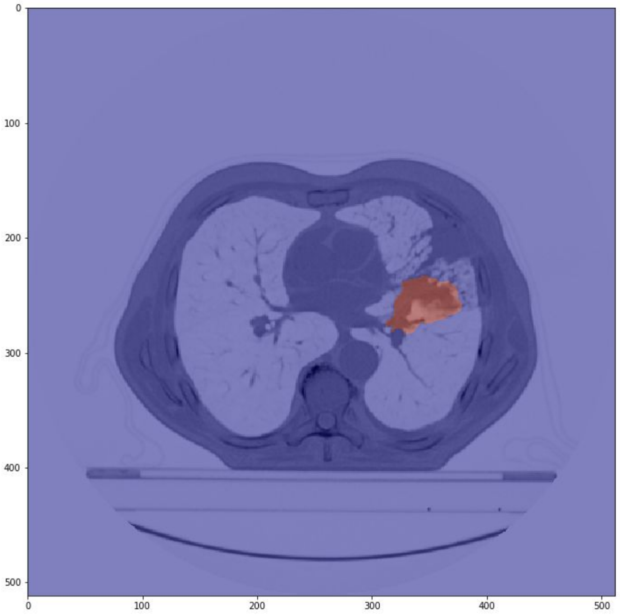


Preliminary Results





Preliminary Results



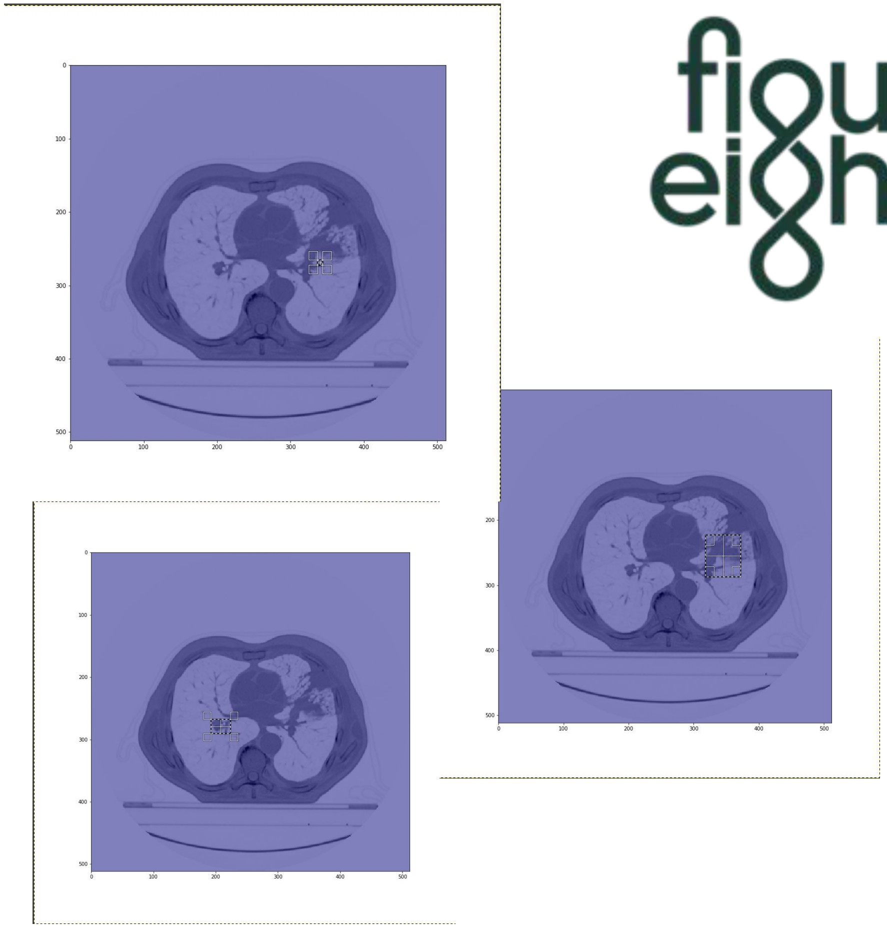


Figure Eight Results & Issues

- 6/15 correctly identified
- Difficult to measure precision in the interface
- Only allow bounding boxes, we require precise contours
- No support for interactive training

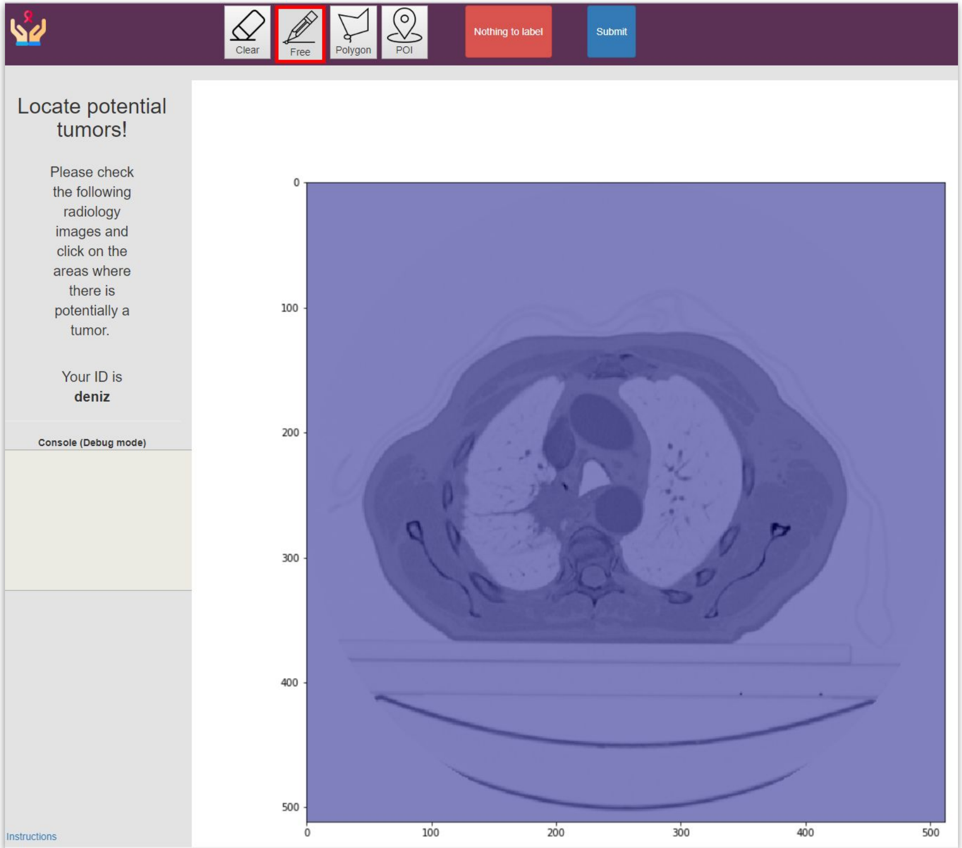
To overcome these issues we need a custom crowdsourcing image annotation software.

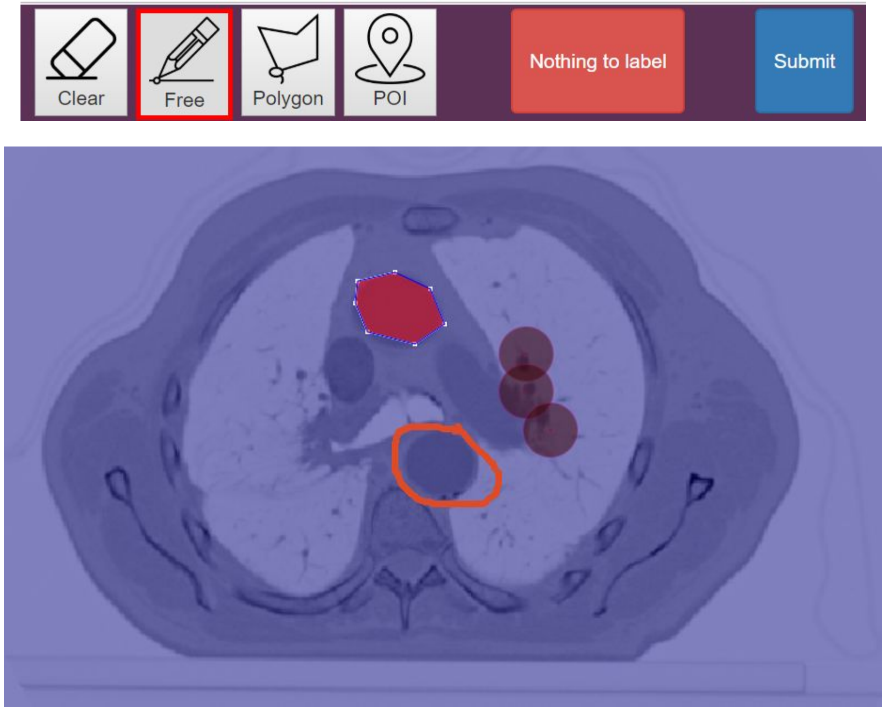
Interactive Interface

- Interactive training
- In-built quality control measures
- Allow the workers to choose different methods for contouring
  - Free hand
  - Polygon
  - Point of interest
- Each HIT consists of 4 microtasks (with 4 different methods)
  - Randomized across HITs
  - Multiple workers per microtask (optimal number determined via CrowdED*)

*_CrowdED: Guideline for Optimal Crowdsourcing Experimental Design_
A Zaveri, PH Serrano, M Desai, M Dumontier. Companion of the The Web Conference 2018 on The Web Conference 2018, 1109-1116

Interactive Interface - Design





Quality Assurance & Evaluation

- threshold of contour overlap with experts
- comparison of different methods of contouring
- comparison of cost and time of annotation between experts and non-experts

Expected Results

- Determine the **feasibility** of using non-experts for contouring clinical images
- Learn how non-experts **compare** with respect to expert annotated images in the precise contouring of images along with costs and time involved by each group.
- **Complete** annotated dataset of the Cancer Imaging Archive collection on lung cancer
- A **scalable and reproducible methodology** that can be re-used in other use cases by researchers with similar research questions
- Feed data into an existing **Machine Learning** image recognition software developed at BISS

Impact

- Annotated data can be fed into **machine learning** algorithms* to increase precision of automated contouring
- **Identify the best treatment** (in terms of survival and quality of life) for the patients
- Enable patients to be properly informed about each treatment option and has the potential to **save lives and increase quality of life for cancer patients**

*Bradley J. Erickson, Panagiotis Korfiatis, Zeynettin Akkus,Timothy L. Kline. Machine Learning for Medical Imaging. Radiographics. 2017

Questions?

http://bit.ly/medical-image-annotation

Arthur Jochems

Deniz Iren

Amrapali Zaveri

BE the crowd !

Your chance to contribute !

Instructions

1) Go to http://out5.net/workshop/
   a) Find your name on the list and click on it. You will be redirected to the annotation platform.
2) Check the instructions, and positive and negative examples.
3) Start the interactive **training session**
   a) Interact with the platform,
   b) Annotate and **check the accuracy** your annotations,
   c) Keep an eye on the Normal CT Scan of the Chest (upper-right corner)
   d) Complete the 11 step training. **Begin annotating**!
4) Complete the annotation tasks (50 in total)
   a) **Submit** your annotation or mark **Nothing to label** if you do not see a tumor.
   b) Check the overall progress
   c) You can take the training again using the link on the bottom-left corner