

# End-to-End Automated Medical Image Analysis on the UCSF Clinical PACS

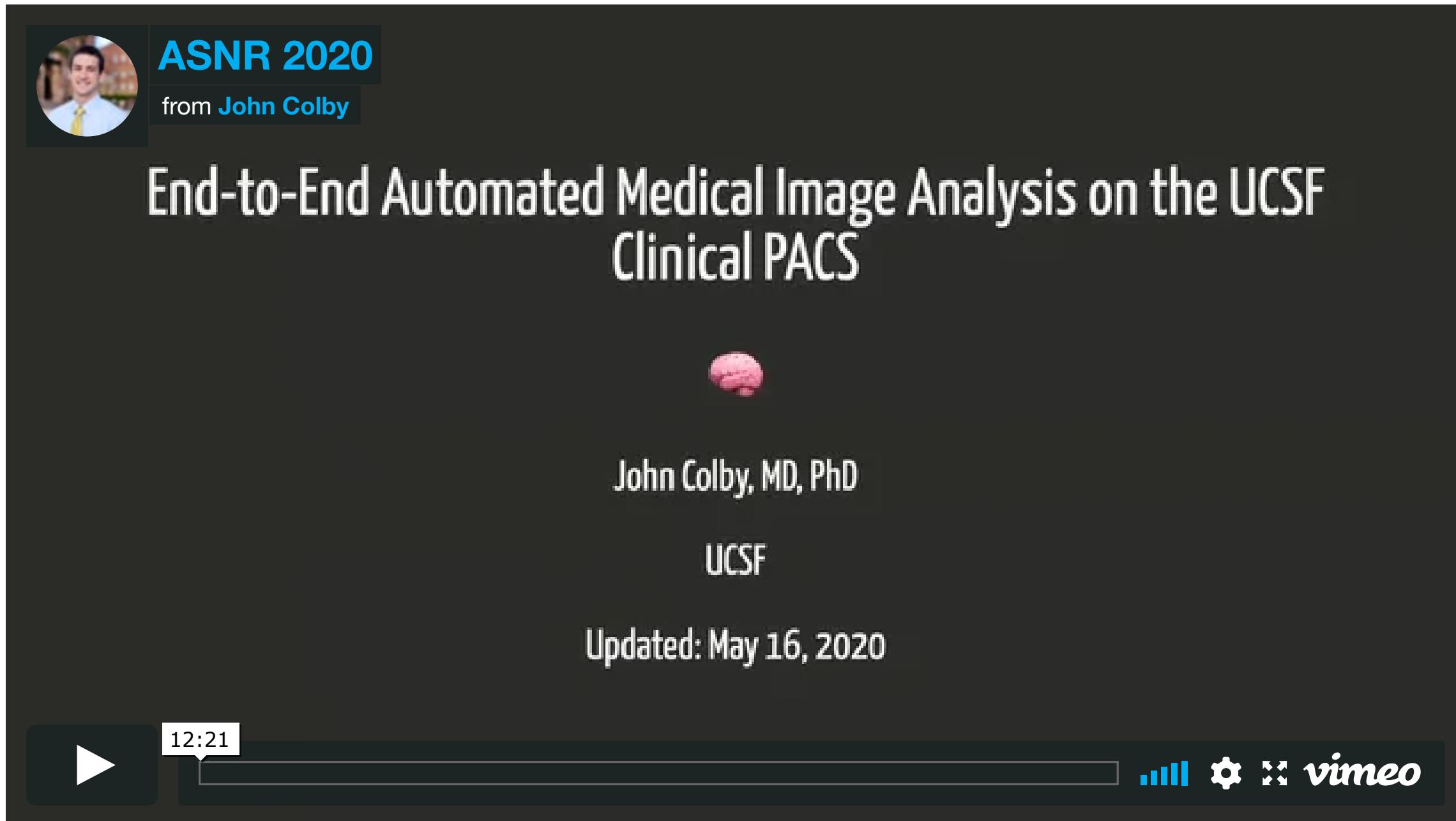


John Colby, MD, PhD

UCSF

Updated: May 17, 2020

# Video presentation



# More info

- Slides: [johncolby.github.io/asnr2020](https://johncolby.github.io/asnr2020)
- Repo: [github.com/johncolby/asnr2020](https://github.com/johncolby/asnr2020)

# Rationale

- Algorithms are free.

kaggle

Search

Featured Prediction Competition

## RSNA Intracranial Hemorrhage Detection

Identify acute intracranial hemorrhage and its subtypes

RSNA Radiological Society of North America · 1,345 teams · 6 months ago

Overview Data Notebooks Discussion Leaderboard Rules Team

Vopani

Gold Medal Solutions

posted in RSNA Intracranial Hemorrhage Detection 6 months ago

List of all gold medal solutions shared:

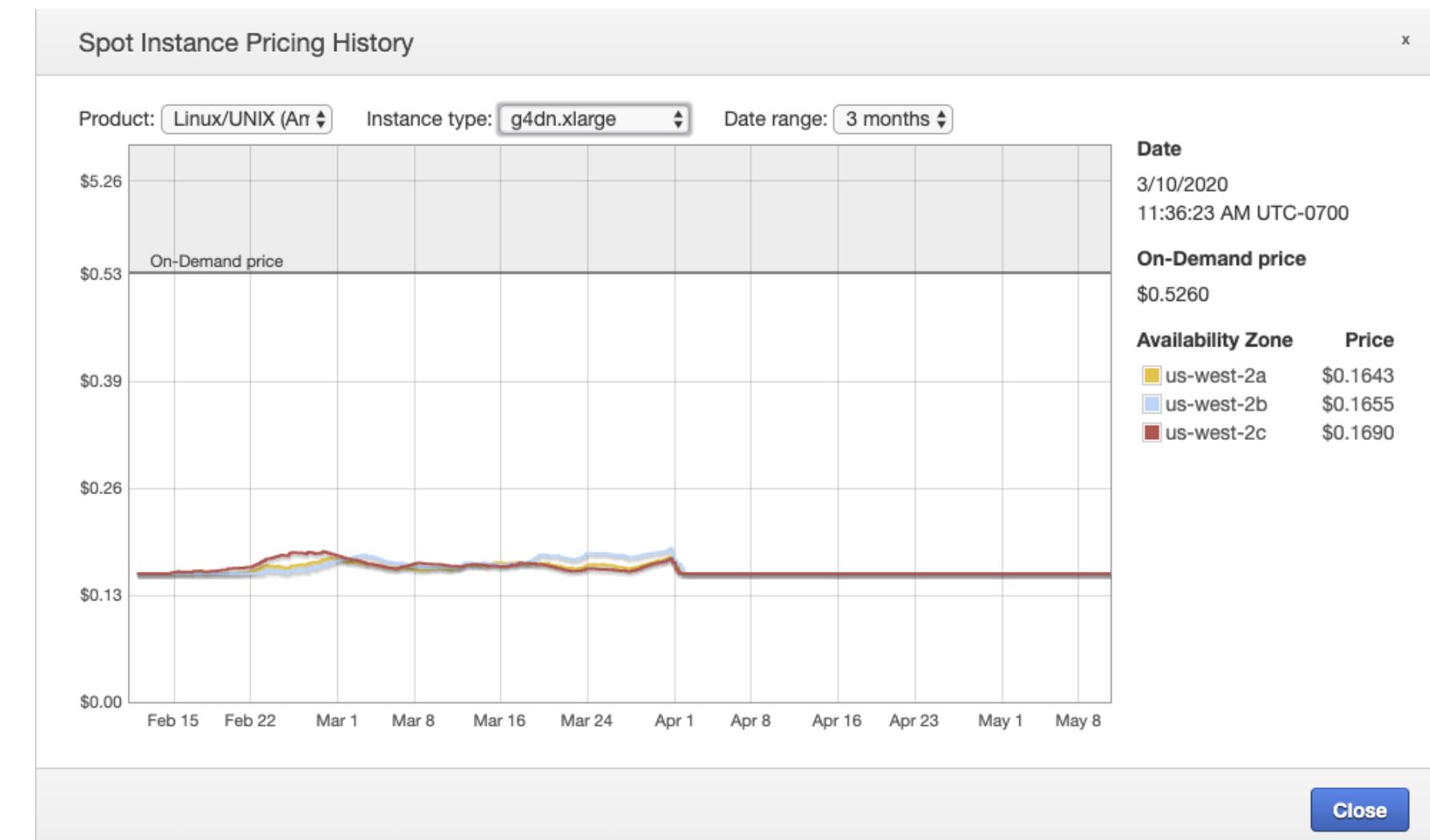
- 1st place solution by Seutao (GitHub)
- 2nd place solution by Darragh (GitHub)
- 3rd place solution by takuoko (GitHub)
- 4th place solution by Miranda X (GitHub)
- 5th place solution by Bac Nguyen (GitHub)
- 6th place solution by DavidGbodiOdaibo
- 7th place solution by Guanshuo Xu
- 8th place solution by Maciej Budyś (GitHub)
- 9th place solution by Andres Torrubia (GitHub)
- 10th place solution by shimacos (GitHub)
- 11th place solution by Appian (GitHub)
- 12th place solution by yuval reina (GitHub)



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San Francisco

# Rationale

- Algorithms are free.
- Computers are cheap.



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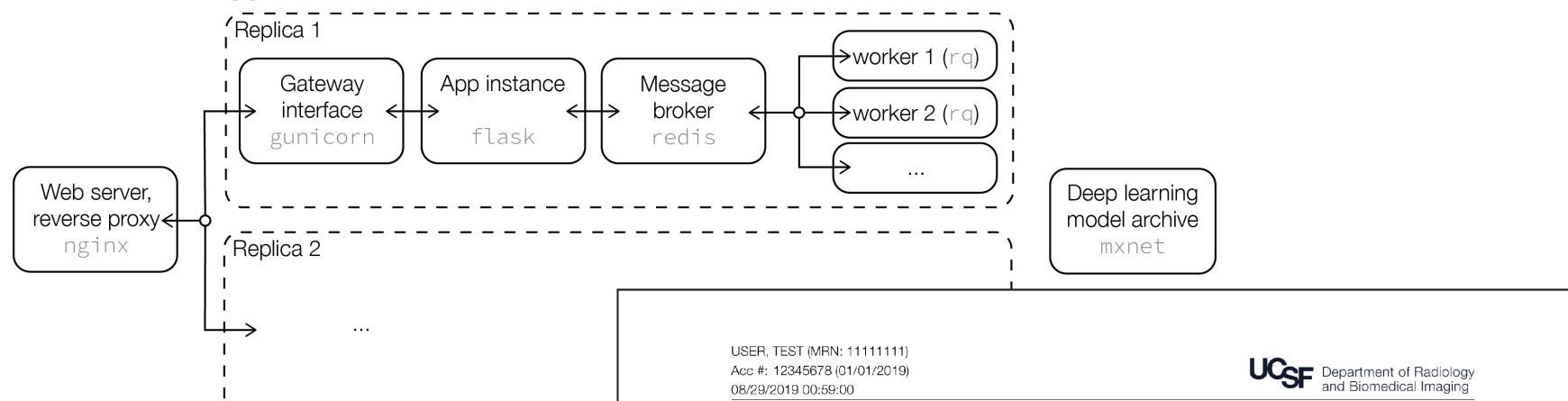
# Rationale

- Algorithms are free.
- Computers are cheap.
- Data are *expensive*.

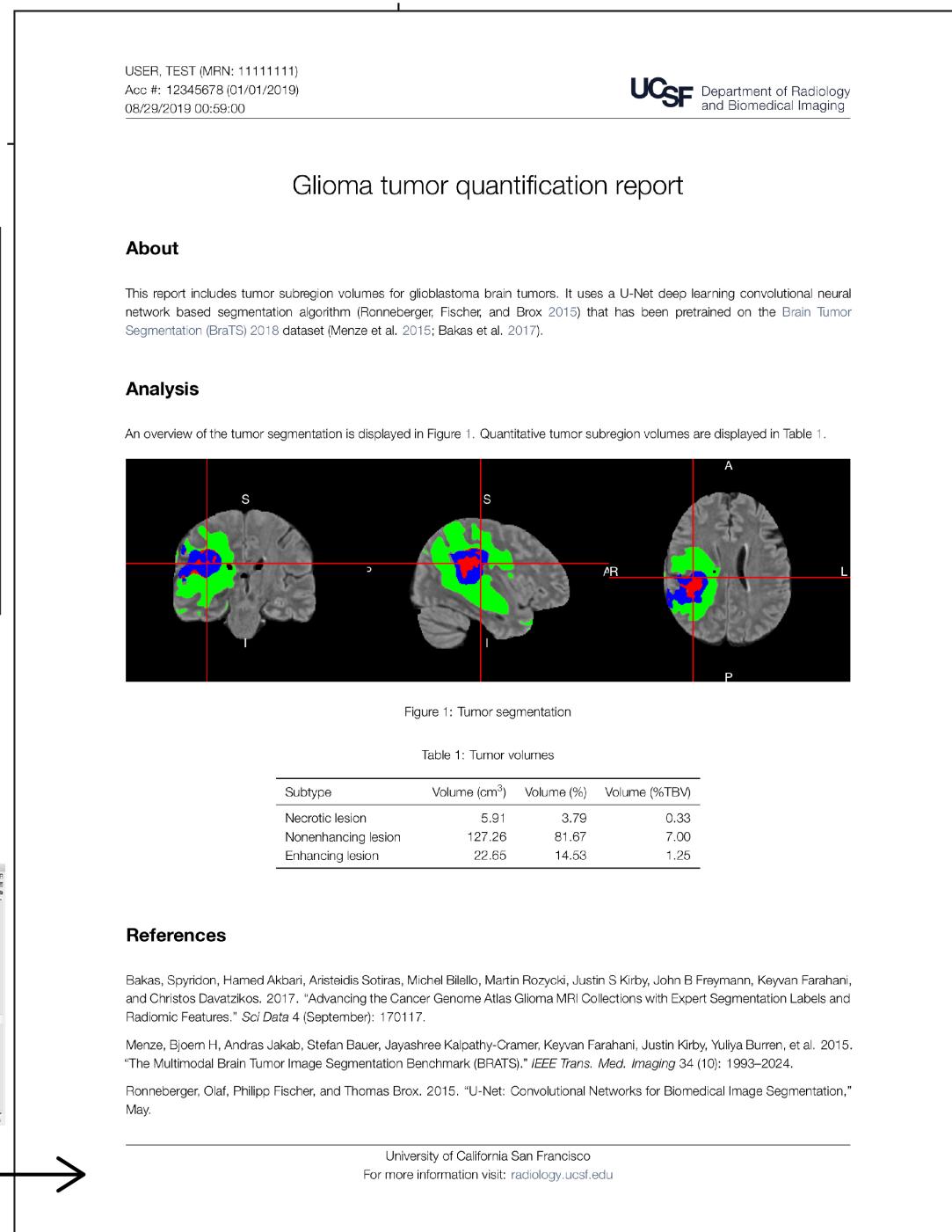
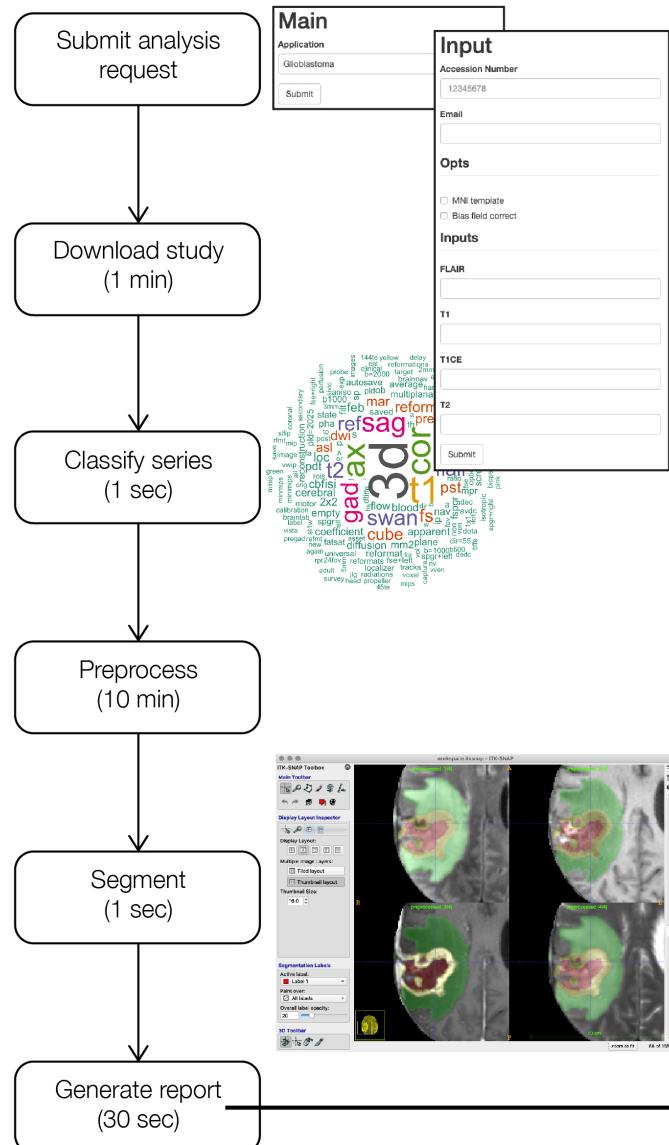


# Overview

## Containerized application framework



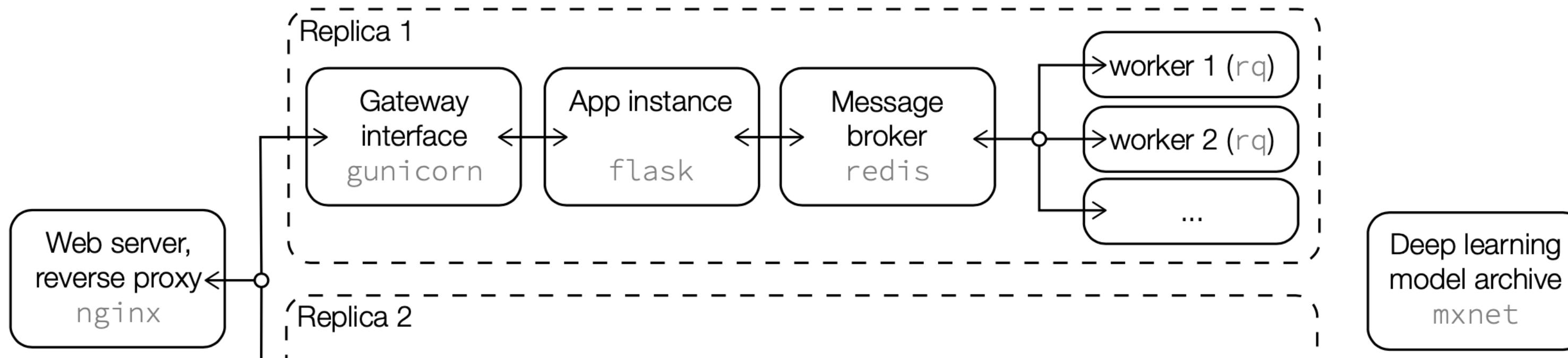
## Example glioma application output



# Extensible application framework

- [johncolby/rad\\_apps](#)
- Simple web frontend.
- API for submitting analysis requests.
- Docker/swarm for scalability and redundancy.
- Can extend base application plugin template for different uses.

## Containerized application framework



# Wrangle data

- [johncolby/dcmclass](#): R package for classifying series from DICOM header metadata (study description, TR, TE, scanner code, etc.)

The image shows a vertical arrangement of text elements. At the top, the word "bravo" is written in large, bold, orange letters. Below it, the letters "t1" and "pre" are in blue, with "brainlab" in green underneath. To the right, "brainnav" is in green, with "st1w" and "sense" in blue underneath. Above "brainnav", there is a red "fs" followed by "spgr" and "t2". To the left of "bravo", the letters "3d" and "ax" are in black. To the right, "gad" is in black, with "fatsat" in blue underneath. Further down, the letters "t1" and "post" are in black, with "data" and "sense" in blue underneath. To the left, "3d" and "ax" are in black. At the bottom, "gad" is in black, with "repeat" in green to its left. The entire composition is set against a white background.

**t2w** data  
**cube** ssfse  
**ref** fse reformat  
gad  
ax  
t2  
ref<sup>tse</sup>  
post  
3d nav  
3mm

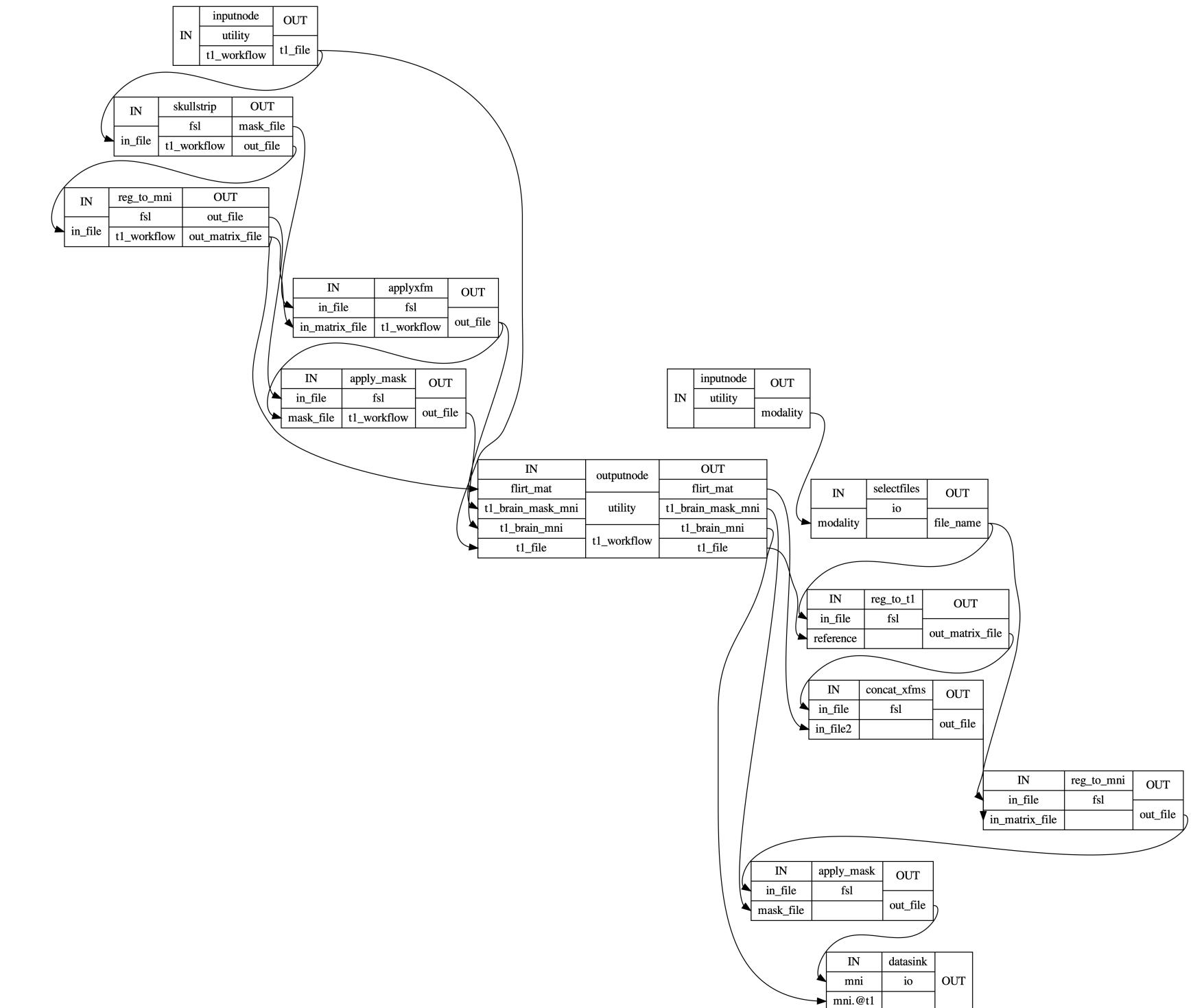
reconstruction  
average  
mm2  
sense  
ref<sup>reform</sup>  
cube  
flair  
ax  
t2  
3d  
reformats  
multiplanar  
><sub>sp</sub><sup>th</sup>  
diffusion mpr  
apparent vif  
vrip  
vrip

T1, T2, T1 post, FLAIR

## other series

# Preprocessing

- Can be trivial (straight DICOMs).
- More complex analyses need more complex preprocessing.
- E.g. multichannel tumor segmentation.
- Mature pipelining tools already exist in the neuroimaging community: **nipype**



# Deep learning inference

- Many modern workflows use DL models, and can benefit from GPUs.
- Can make sense to split off from the rest of processing.
- [aws-labs/multi-model-server](#)
  - Containerized, scalable, DL model server.
  - *[A flexible and easy to use tool for serving deep learning models trained using any ML/DL framework.]*
  - Open Neural Network Exchange (ONNX): Compatibility between torch, mxnet, tensorflow, etc.

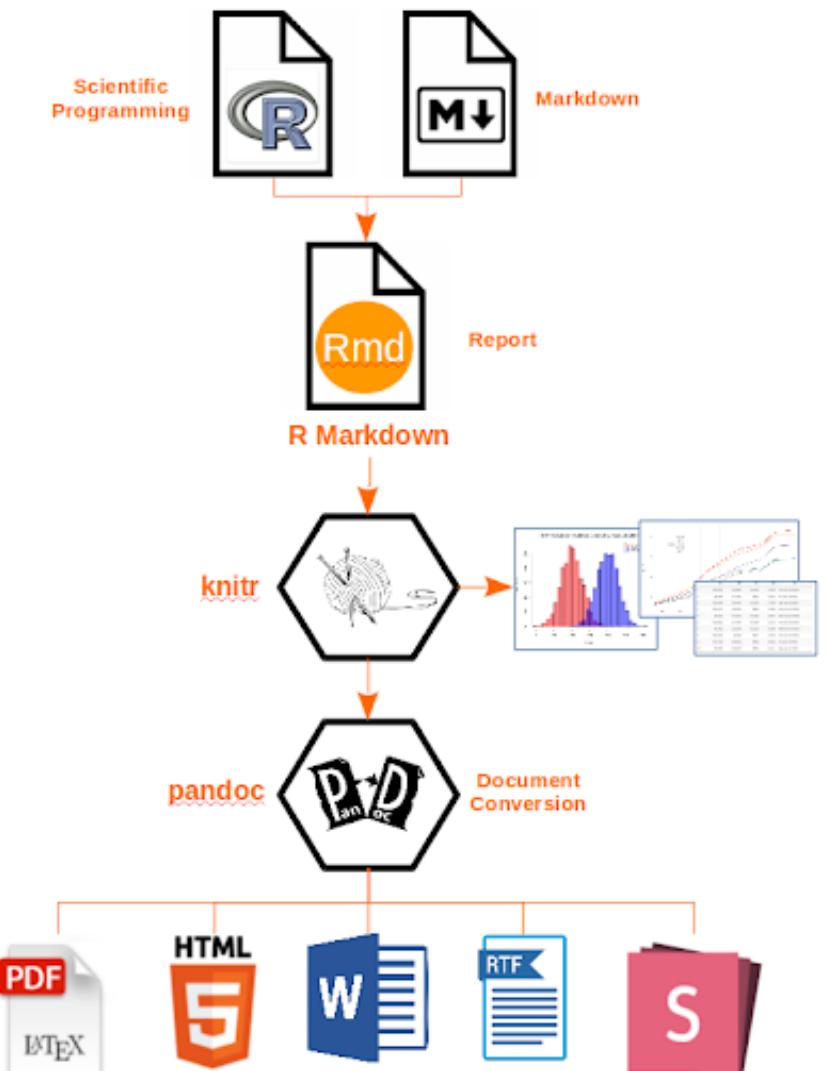
# Report

USER, TEST (MRN: 11111111)  
Acc #: 12345678 (01/01/2019)  
08/29/2019 00:59:00

**UCSF** Department of Radiology  
and Biomedical Imaging

## Glioma tumor quantification report

- R Markdown.
- Reproducible, dynamic, analysis reports.
- Mix prose, stats, visualization.
- Can output to web, PDF, others



### About

This report includes tumor subregion volumes for glioblastoma brain tumors. It uses a U-Net deep learning convolutional neural network based segmentation algorithm (Ronneberger, Fischer, and Brox 2015) that has been pretrained on the Brain Tumor Segmentation (BraTS) 2018 dataset (Menze et al. 2015; Bakas et al. 2017).

### Analysis

An overview of the tumor segmentation is displayed in Figure 1. Quantitative tumor subregion volumes are displayed in Table 1.

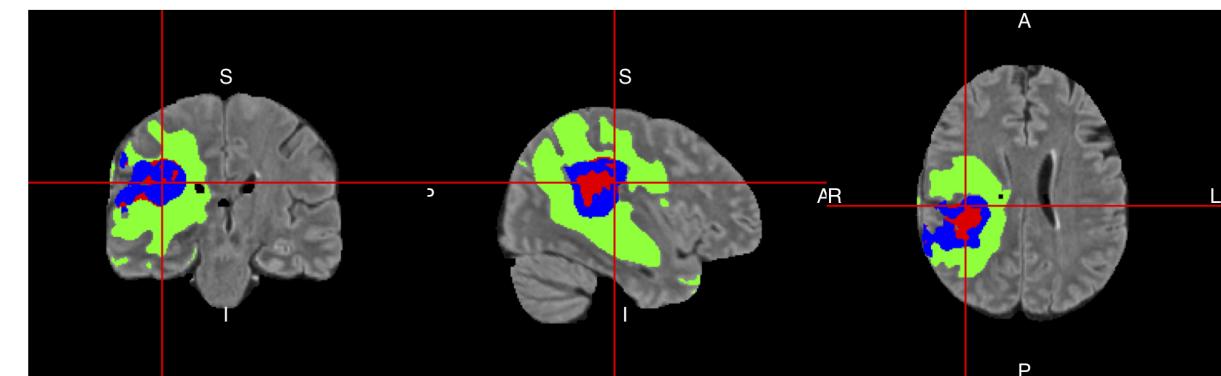


Figure 1: Tumor segmentation

Table 1: Tumor volumes

Subtype	Volume (cm³)	Volume (%)	Volume (%TBV)
Necrotic lesion	5.91	3.79	0.33
Nonenhancing lesion	127.26	81.67	7.00
Enhancing lesion	22.65	14.53	1.25

### References

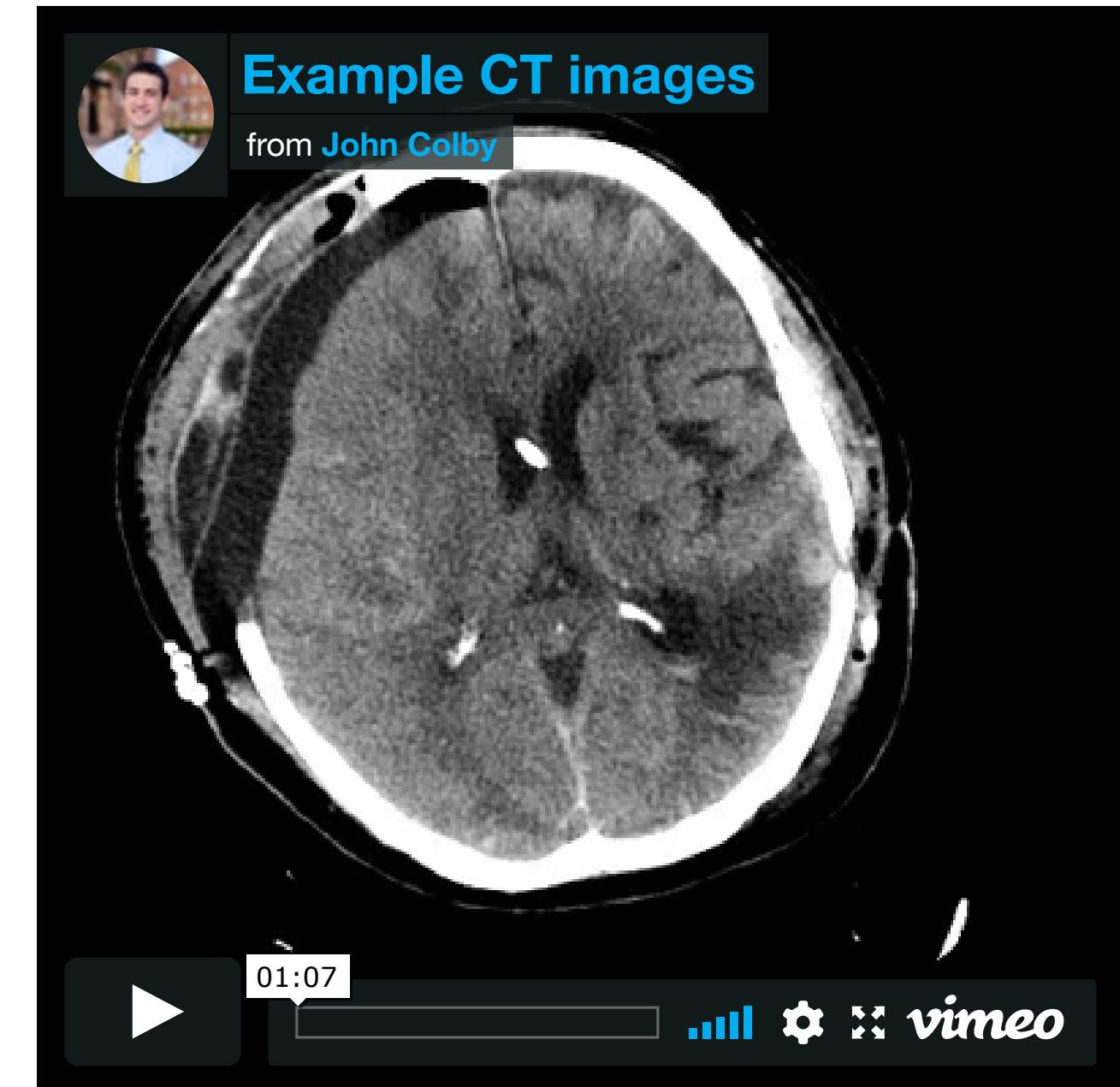
Bakas, Spyridon, Hamed Akbari, Aristeidis Sotiras, Michel Bilello, Martin Rozycski, Justin S Kirby, John B Freymann, Keyvan Farahani, and Christos Davatzikos. 2017. "Advancing the Cancer Genome Atlas Glioma MRI Collections with Expert Segmentation Labels and Radiomic Features." *Sci Data* 4 (September): 170117.

Menze, Bjoern H, Andras Jakab, Stefan Bauer, Jayashree Kalpathy-Cramer, Keyvan Farahani, Justin Kirby, Yuliya Burren, et al. 2015. "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)." *IEEE Trans. Med. Imaging* 34 (10): 1993–2024.

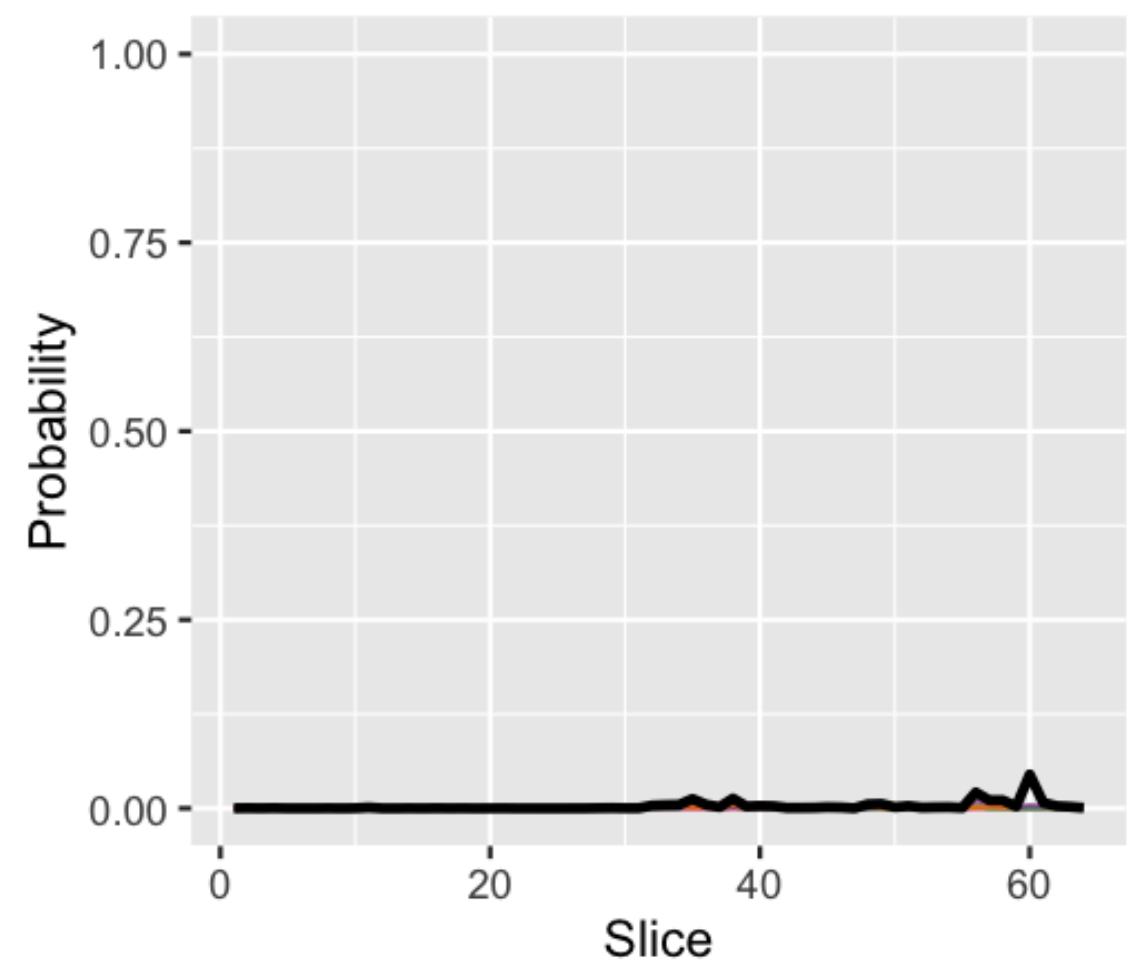
Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. 2015. "U-Net: Convolutional Networks for Biomedical Image Segmentation," May.

# Example: Hemorrhage detection at noncontrast CT

- RSNA Intracranial Hemorrhage Detection challenge
- Hemorrhage ∈ [none, any, epidural, intraparenchymal, intraventricular, subarachnoid, subdural]
- 2D CNN deep learning model  
[johncolby/rsna\\_heme](https://github.com/johncolby/rsna_heme)



# Negative 1

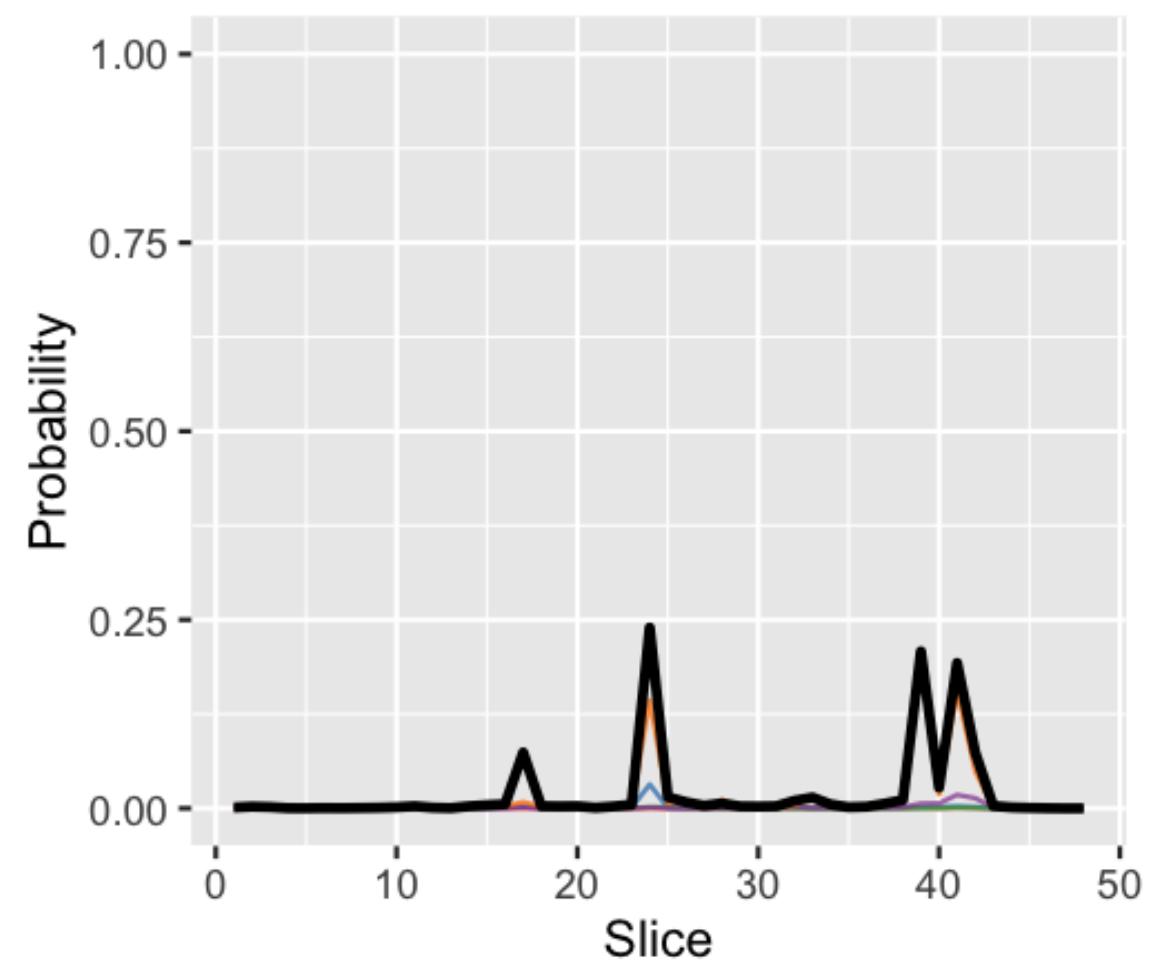


Hemorrhage type

- epidural
- intraparenchymal
- intraventricular
- subarachnoid
- subdural



# Negative 2

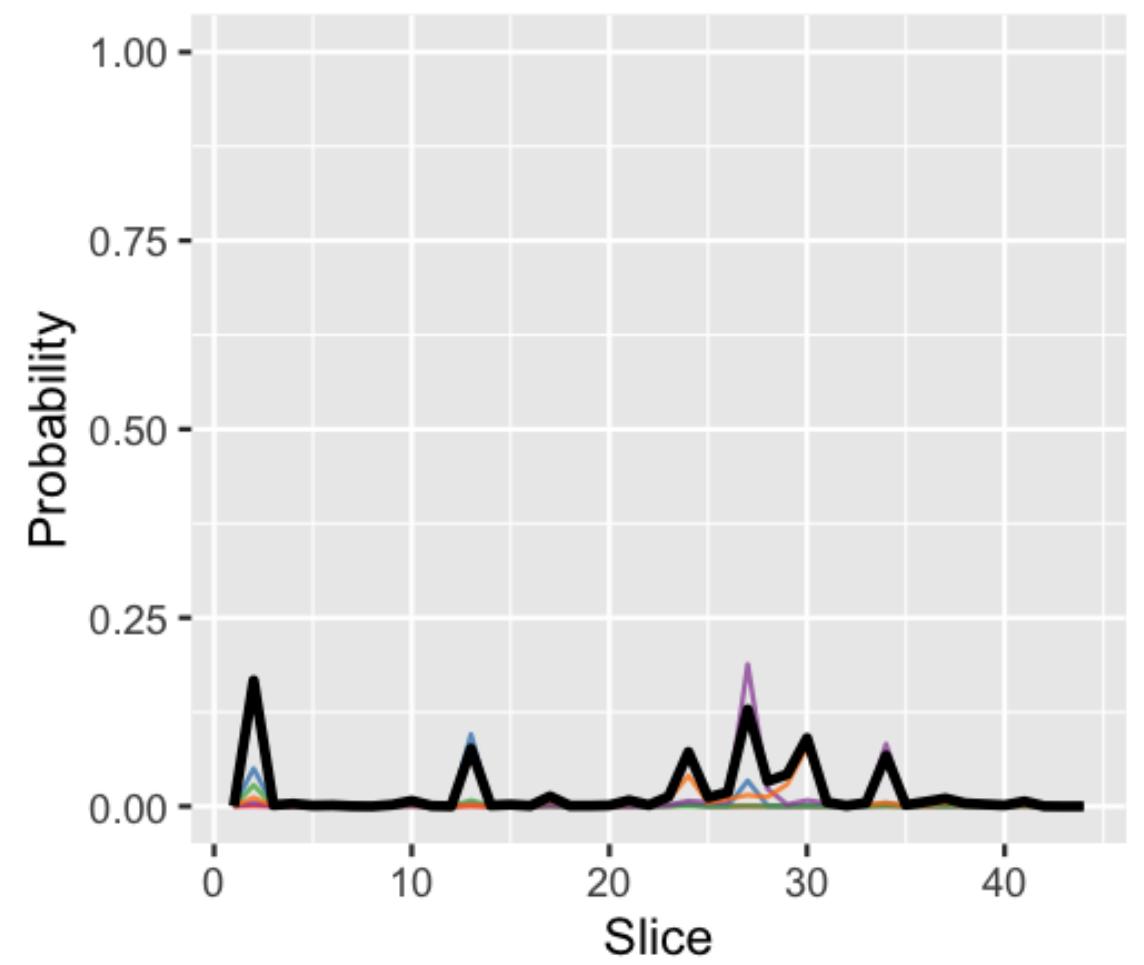


Hemorrhage type

- epidural
- intraparenchymal
- intraventricular
- subarachnoid
- subdural



# Negative 3

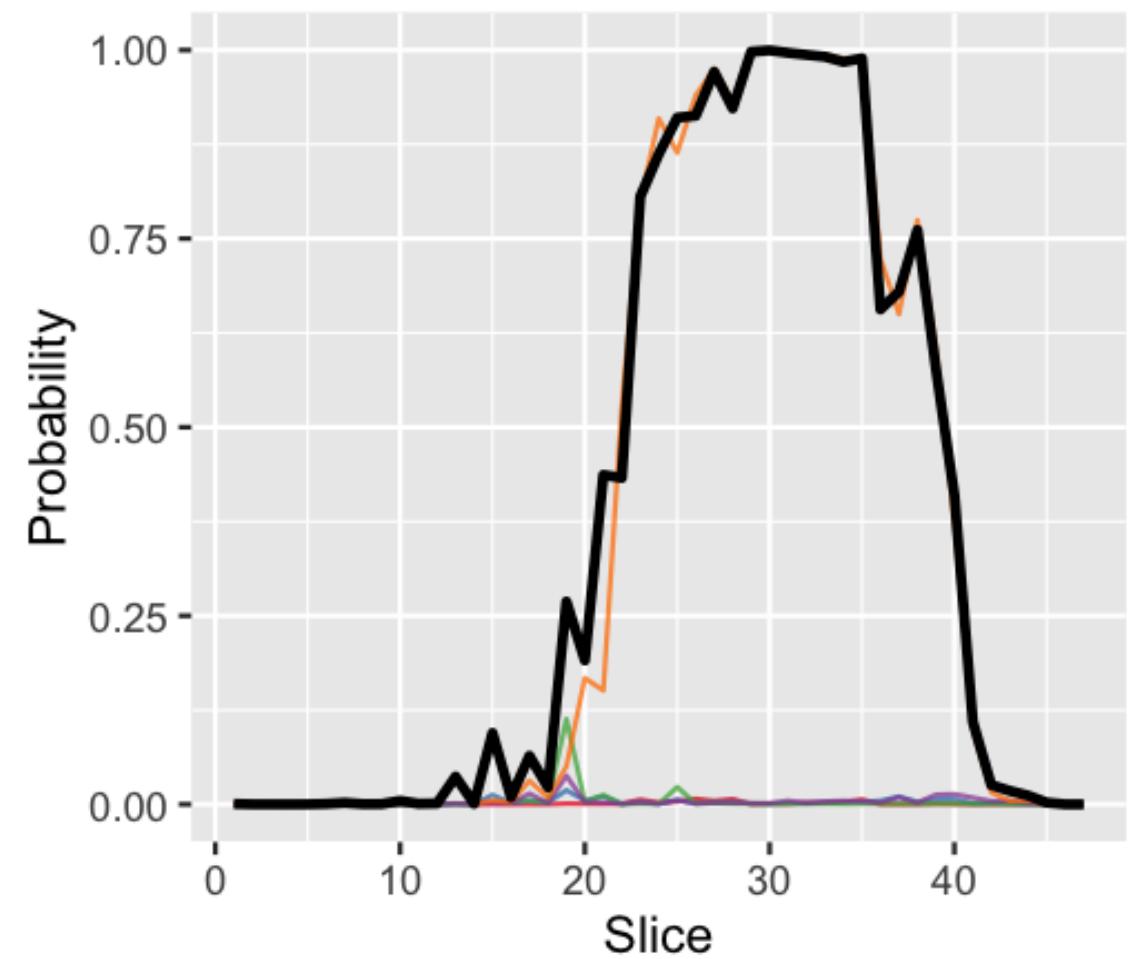


Hemorrhage type

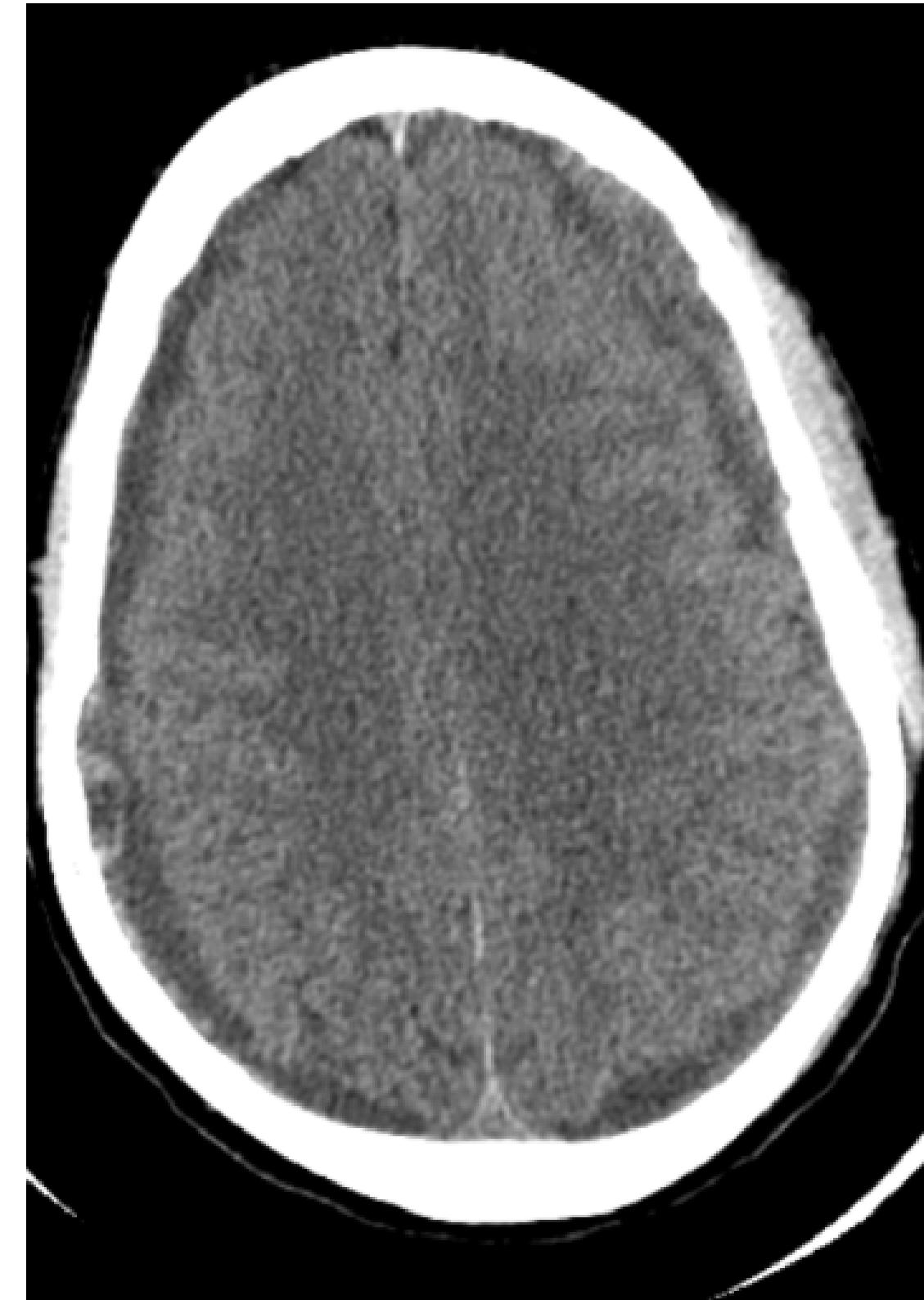
- epidural
- intraparenchymal
- intraventricular
- subarachnoid
- subdural



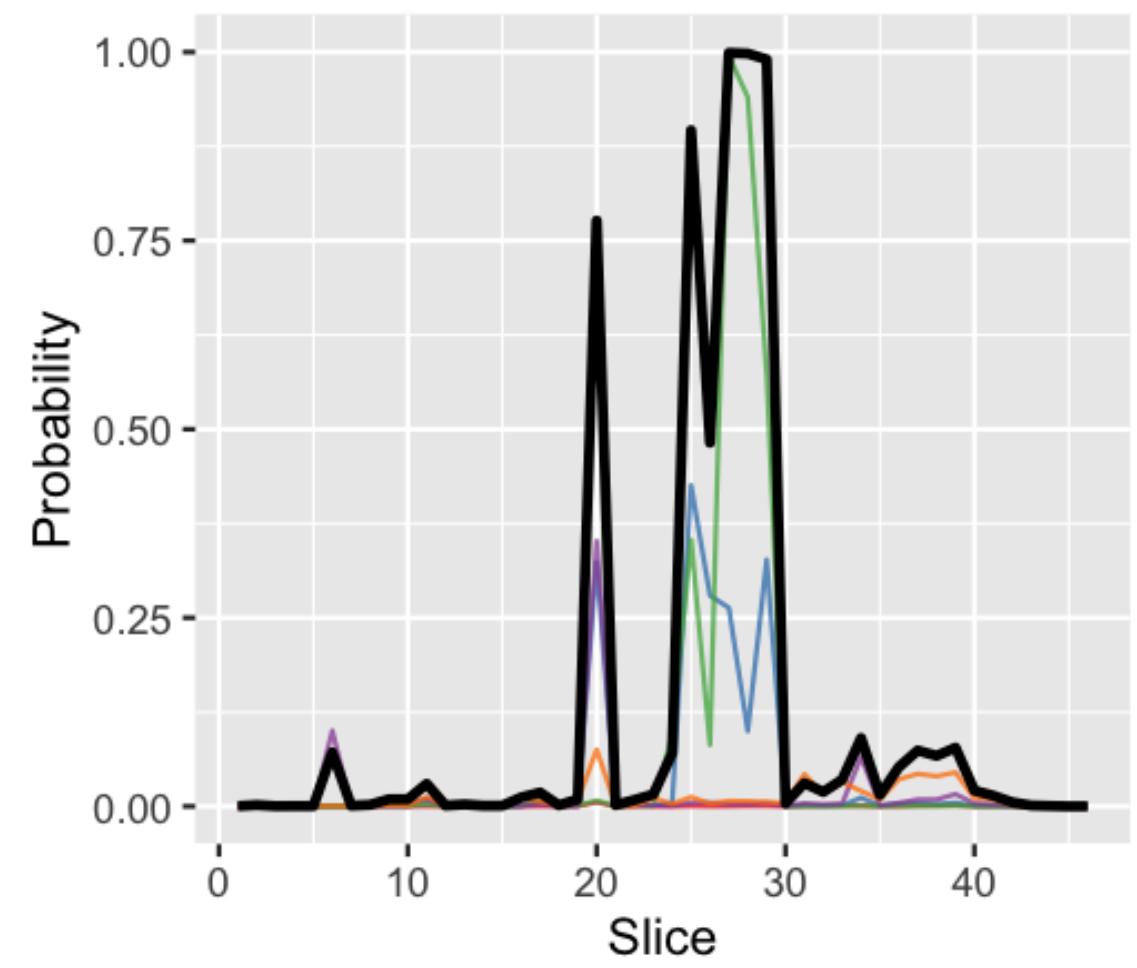
# Subdural



- Hemorrhage type
- epidural
  - intraparenchymal
  - intraventricular
  - subarachnoid
  - subdural



IVH



#### Hemorrhage type

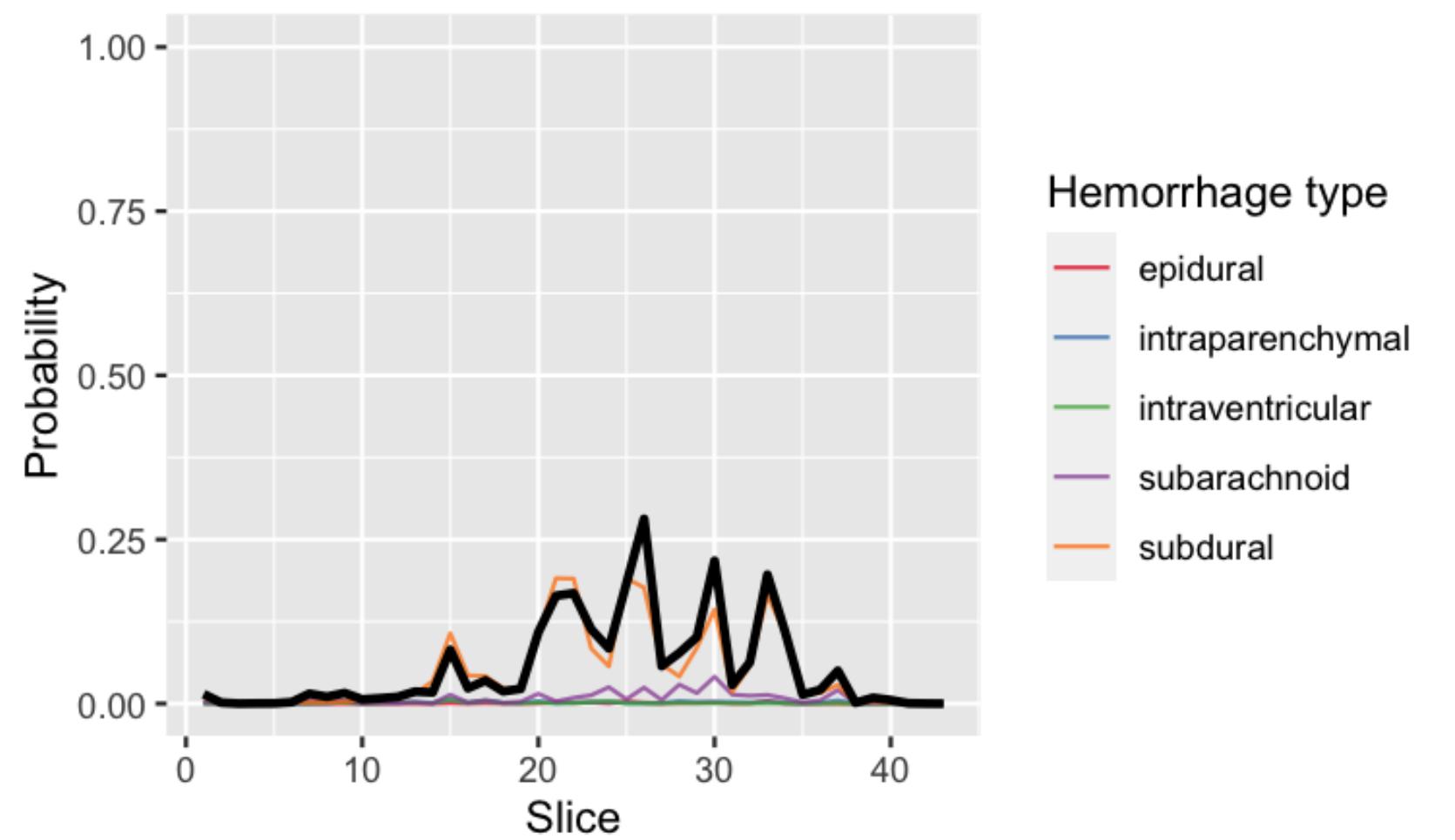
- epidural
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- subarachnoid
- subdural



UCSF

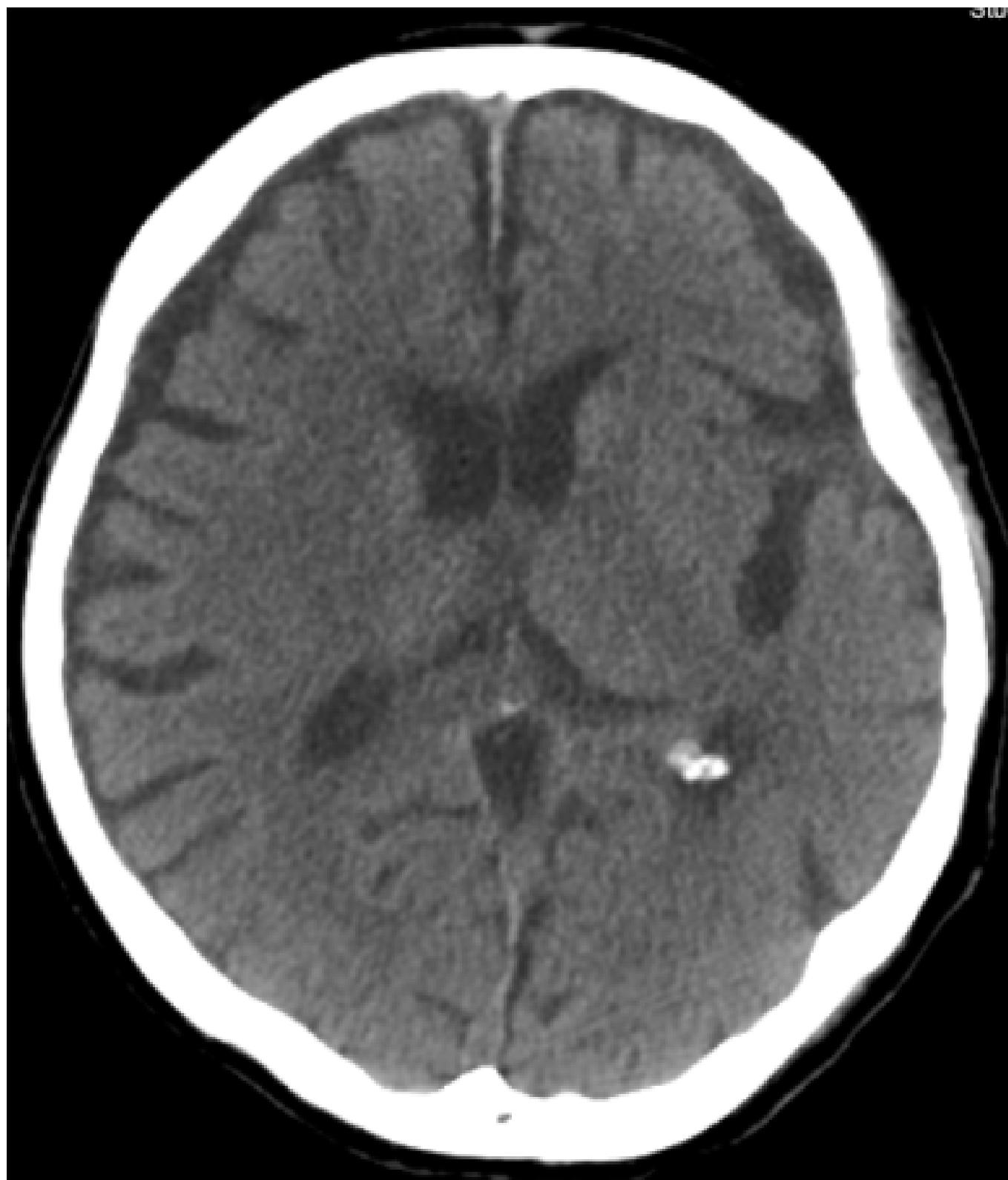
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San Francisco

# Atrophy

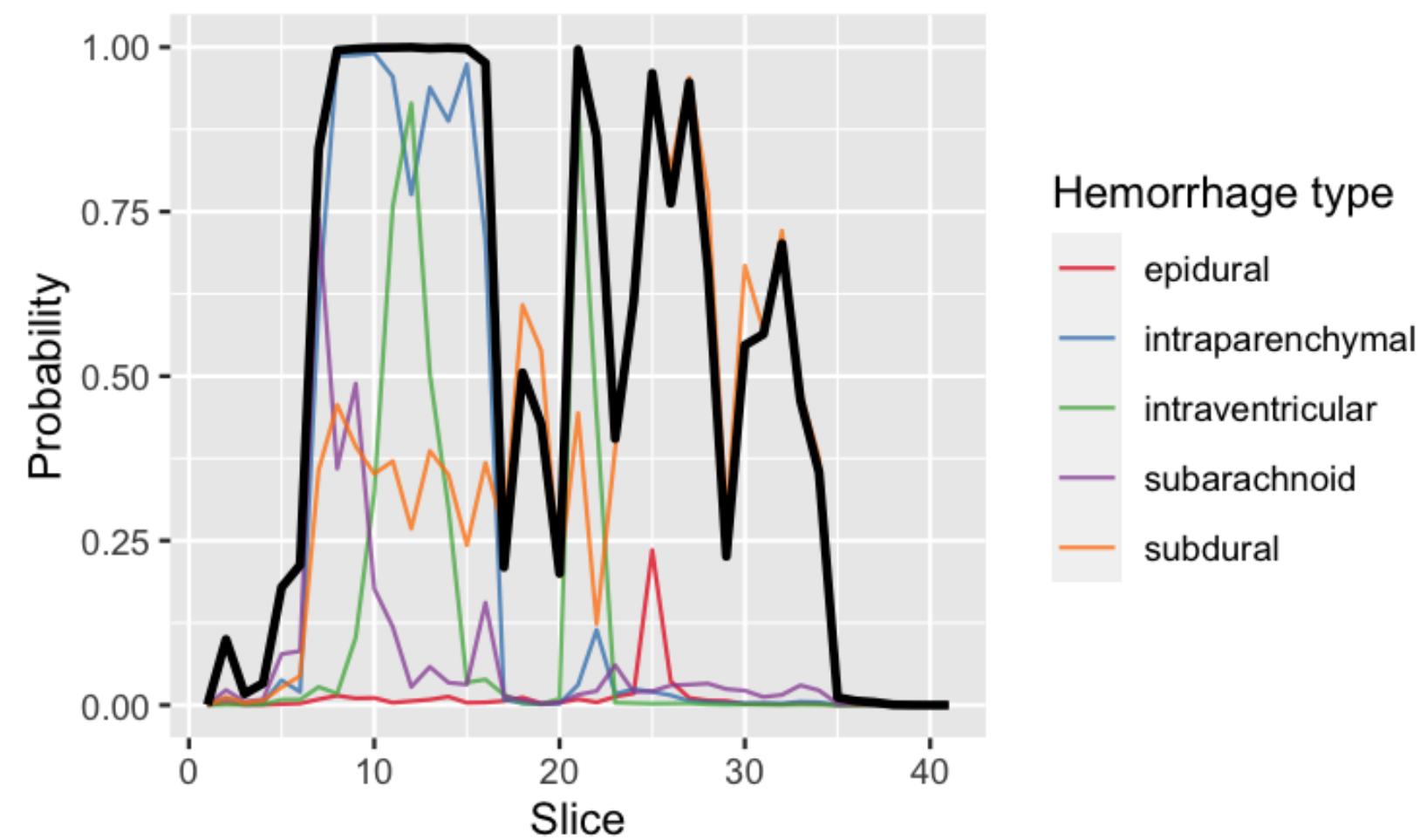


Hemorrhage type

- epidural
- intraparenchymal
- intraventricular
- subarachnoid
- subdural



# Post-op



Hemorrhage type

- epidural
- intraparenchymal
- intraventricular
- subarachnoid
- subdural



# Live app server

Main

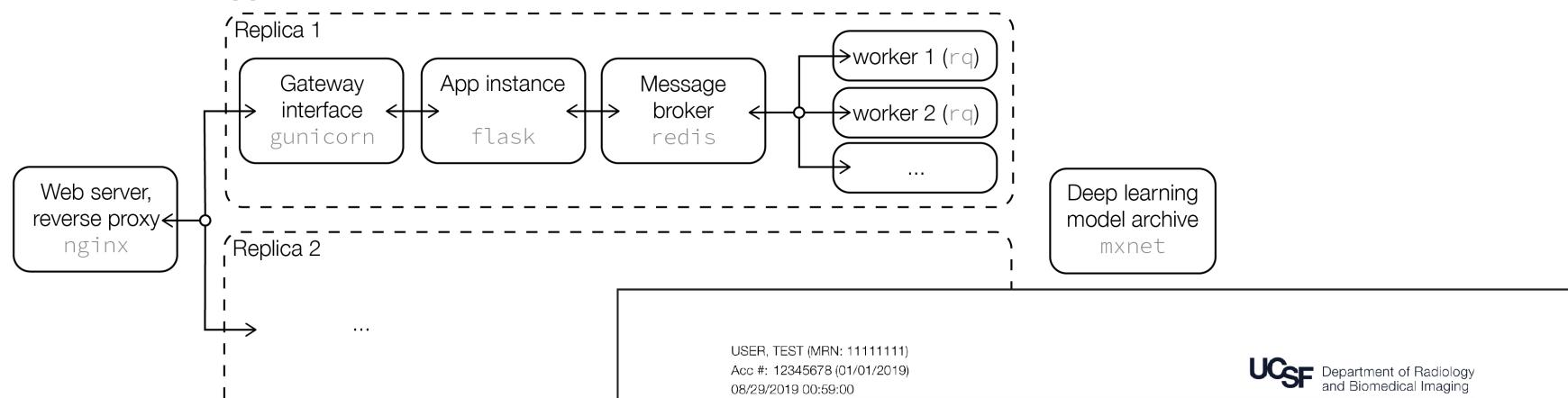
Application

NCHCT hemorrhage

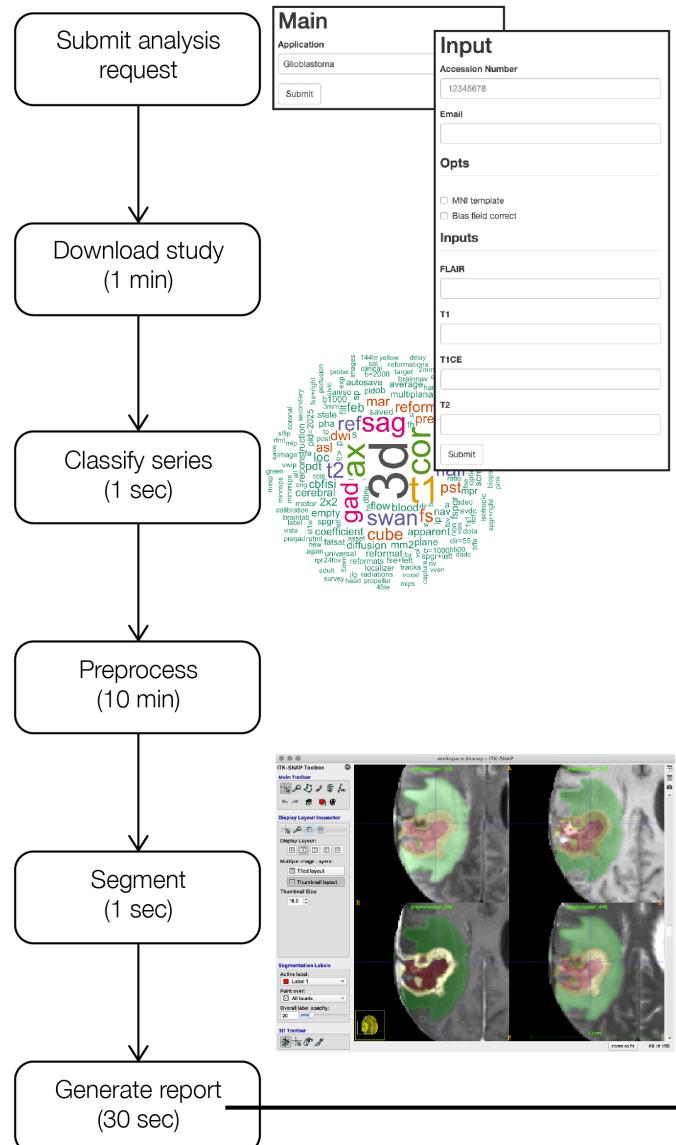
Submit

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University of California San Francisco  
For more information visit: [radiology.ucsf.edu](http://radiology.ucsf.edu)

# Thanks!

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