Predicting hemorrhage related outcomes with CT volumetry for traumatic hemothorax

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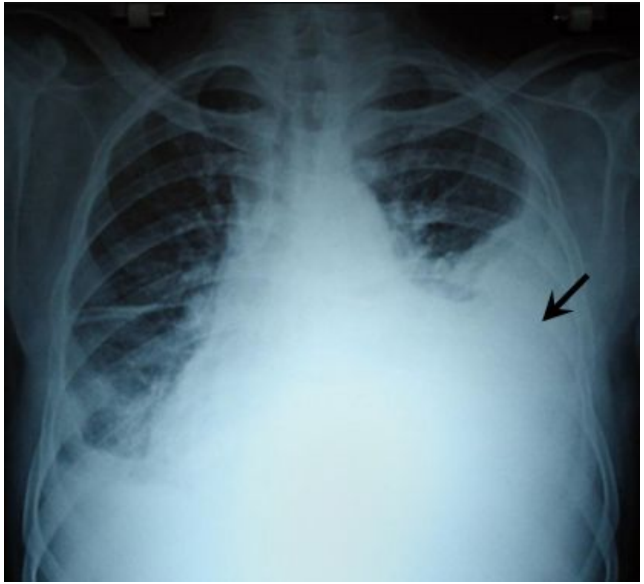
Mentors:

- David Dreizin, MD
- Mathias Unberath, PhD

The Project

We are developing an automated method of quantifying blood volume from CT scans of patients with hemothoraces (accumulation of blood in the pleural sac surrounding the lungs). To do this, deep segmentation networks are used to extract hemothorax pixels from each image slice to ultimately sum the segmented voxels.



https://en.wikipedia.org/wiki/Hemothorax

Clinical Motivation

There needs to be a model for predicting trauma-related outcomes, such as hemorrhage and mortality. The decision tool, which can also be used for prognosis, will help doctors prepare the need for massive blood transfusion, surgical catheter-based intervention, or chest tube for blood drainage.

Prior Work

- Prior models that studied pleural effusion (excess liquid in general, including blood and water), a condition comparable to hemothorax, are generally rule-based or atlas-based [1].
    - Insufficient at handling anatomical distortions, including the heterogeneity of attenuation and traumatic lung problems.

- U-net/3D U-net is popular for semantic segmentation.
    - Due to the multifocal nature of hemothorax, regular convolutional networks are unlikely to perform well as noted by Dr. Dreizin [2].

[1] Yao, J., Bliton, J., & Summers, R. M. (2013). Automatic segmentation and measurement of pleural effusions on CT. IEEE transactions on biomedical engineering, 60(7), 1834–1840. https://doi.org/10.1109/TBME.2013.2243446

[2] Dreizin, D., Zhou, Y., Fu, S., Wang, Y., Li, G., Champ, K., Siegel, E., Wang, Z., Chen, T., & Yuille, A. L. (2020). A Multiscale Deep Learning Method for Quantitative Visualization of Traumatic Hemoperitoneum at CT: Assessment of Feasibility and Comparison with Subjective Categorical Estimation. *Radiology. Artificial intelligence*, *2*(6), e190220. https://doi.org/10.1148/ryai.2020190220

Goals

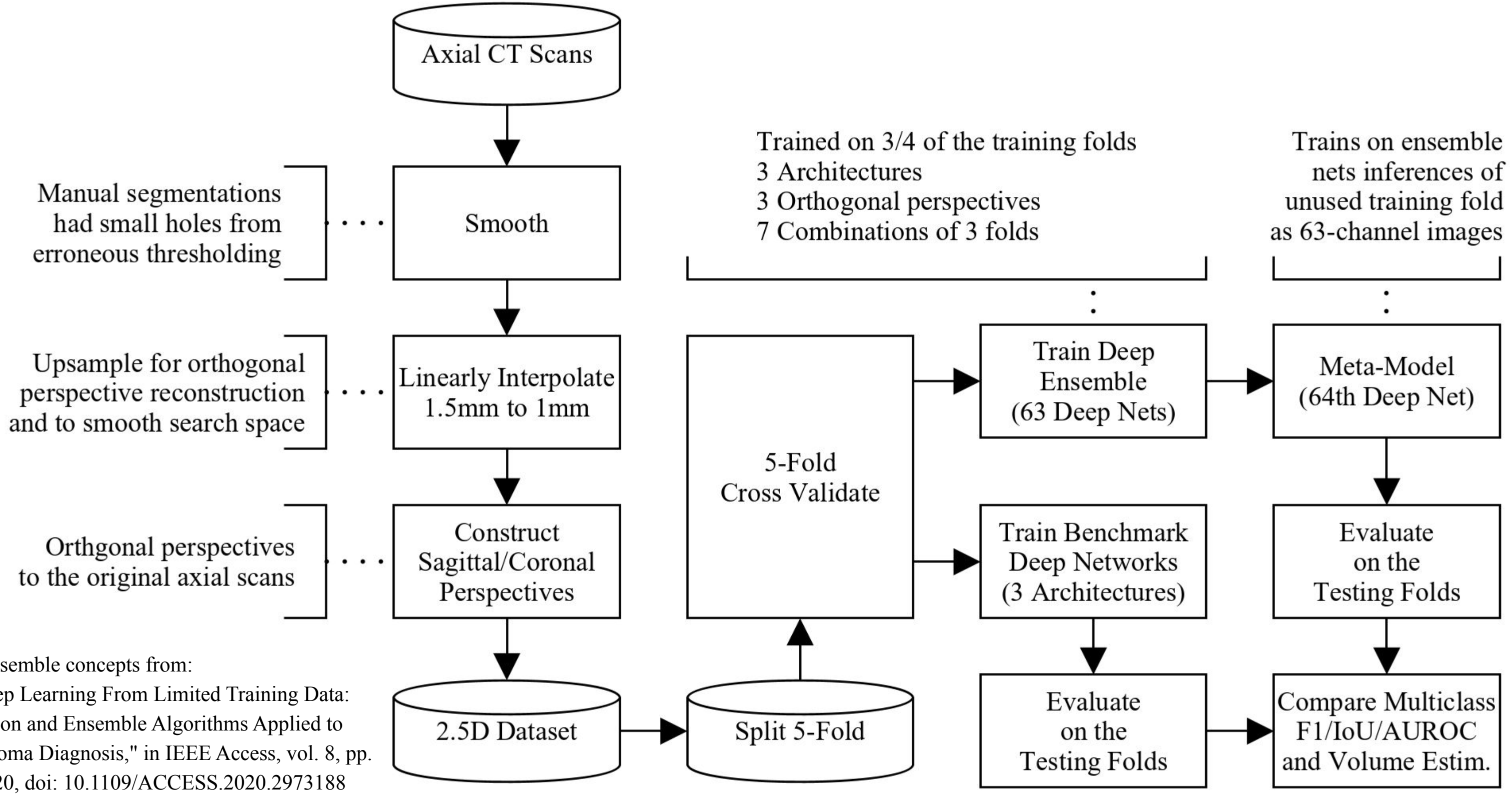
Minimal: An application that takes a set of axial CT scans as input and outputs estimated hemothorax volume (0 if not present).

Expected: An application that quantifies hemothorax blood volume within 5% error from k-fold cross validation

Maximum:

1. An algorithm that, in addition to the expected, can also express a level of certainty and/or is interpretable
2. A graphical application that wraps the train/test code, CT scan visualizations, and confidence level calculation

Technical Approach Overview

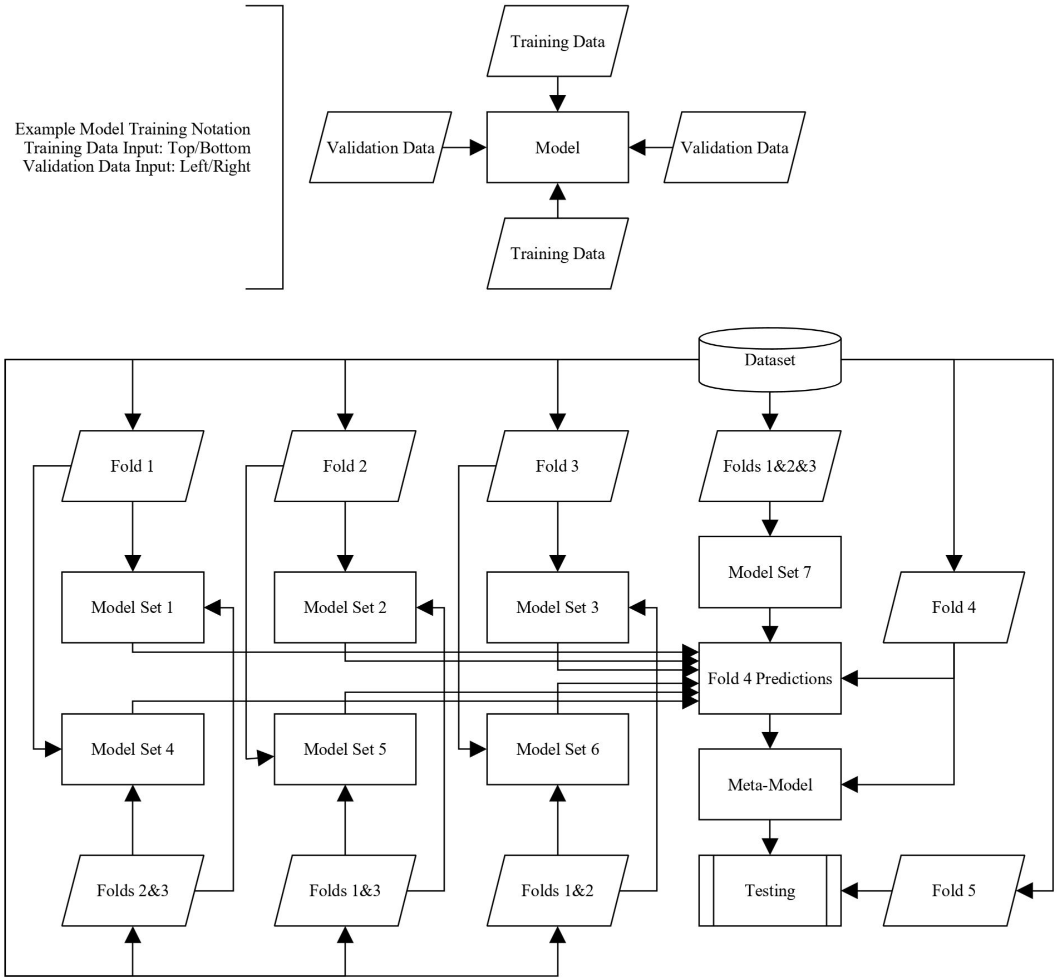


Building off of ensemble concepts from:

B. A. Albert, "Deep Learning From Limited Training Data: Novel Segmentation and Ensemble Algorithms Applied to Automatic Melanoma Diagnosis," in IEEE Access, vol. 8, pp. 31254-31269, 2020, doi: 10.1109/ACCESS.2020.2973188

Ensembling Deep Segmentation Networks

- 5-Fold Cross Validation
- Multiple Network Architectures
  - 3D U-Net [1]
  - V-Net [2]
  - Med3D [3]
- 7 Models Per Arch Per CV
  - 1+2+3 combinations of folds 1-3
  - Fold 4 validates 1-3
  - Fold 5 tests overall
- 1 Meta-Model Network Inferences 63-Channel Ensemble Output
- Total of 5(21Arch+1) Deep Networks



[1] Çiçek Ö, Abdulkadir A, Lienkamp SS, Brox T, Ronneberger O. 3D U-Net: learning dense volumetric segmentation from sparse annotation. In International conference on medical image computing and computer-assisted intervention 2016 Oct 17 (pp. 424-432). Springer, Cham.
[2] Milletari F, Navab N, Ahmadi SA. V-net: Fully convolutional neural networks for volumetric medical image segmentation. In2016 fourth international conference on 3D vision (3DV) 2016 Oct 25 (pp. 565-571). IEEE.
[3] Chen S, Ma K, Zheng Y. Med3d: Transfer learning for 3d medical image analysis. arXiv preprint arXiv:1904.00625. 2019 Apr 1.

Computing Dependency and Logistics

Compute cluster Orthrus to train ~32 models per day from scratch

Stats normalized to MARCC
([Orthrus] : [MARCC GPU nodes])
1:4 FLOPS (both FP32 and FP64)
1:6 GDDR5
1:64 CPU-GPU data transfer rate

https://www.nvidia.com/content/dam/en-zz/Solutions/Data-Center/tesla-product-literature/TeslaK80-datasheet.pdf

Additional Dependencies

Dependency	Need	Status	Followup	Contingency Plan	Planned	Hard
Computing Power	train many models	Orthrus cluster	N/A	Google Cloud Credits	1/28	2/22
CT Scans	train any models	Uploaded to Orthrus	Interpolating to 1mm, building 3 views	N/A	2/18	2/24
CUDA **developer.nvidia.com/cuda-zone**	GPU interface	Installed	N/A	N/A	1/28	2/22
PyTorch **pytorch.org**	setup environment	Installed	N/A	Tensorflow tensorflow.org	N/A	N/A
3D Slicer **slicer.org**	visualize scans	Installed	N/A	Use python packages	N/A	N/A
Open-Source Models	Benchmark and ensemble	Implementing	Run and evaluate	N/A	3/10	3/15

Testing Plan

- Testing of **preprocessing**: The functions to perform interpolation and 3-D slices will be tested using unit tests. We also plan to eye-inspect the result of the preprocessing against the original file to verify the result.
- Testing of **frameworks, pipelines and I/O**s: Those API will be tested mainly through unit tests, and their overall function will be verified and debugged during the training.
- Testing of **models**: All models (including the benchmarks and the ensemble) will be validated using Dice and Jaccard indices, as well as the ROC curve.

Key Activities and Milestones

	Activities	Results/Deliverables
Minimum	Literature survey for model selection	Draft a list of open-source models with code or architecture description
	Preprocess CT scans (interpolate, make 3d slices)	Interpolate CT scans and convert data to PyTorch tensor type
	Complete pipeline and I/O APIs for the project	Build a network framework consists of Python classes
	Benchmark open-source models	Benchmark existing open-source models measured with Dice/Jaccard
Expected	Design and implement an ensemble algorithm	A program that estimates blood volume (inputs: CT axial scans; output: a value)
	Improve the ensemble algorithm	A program outperforms the benchmark (inputs: CT axial scans; output: a value)
Maximum	Implement a GUI-program for visualization	A program incorporates the framework (inputs: CT axial scans; output: segmentation)
	Incorporate certainty level into our algorithm	A program visualizes confidence (input: CT axial scans; output: heatmaps)

Timeline – Project Management

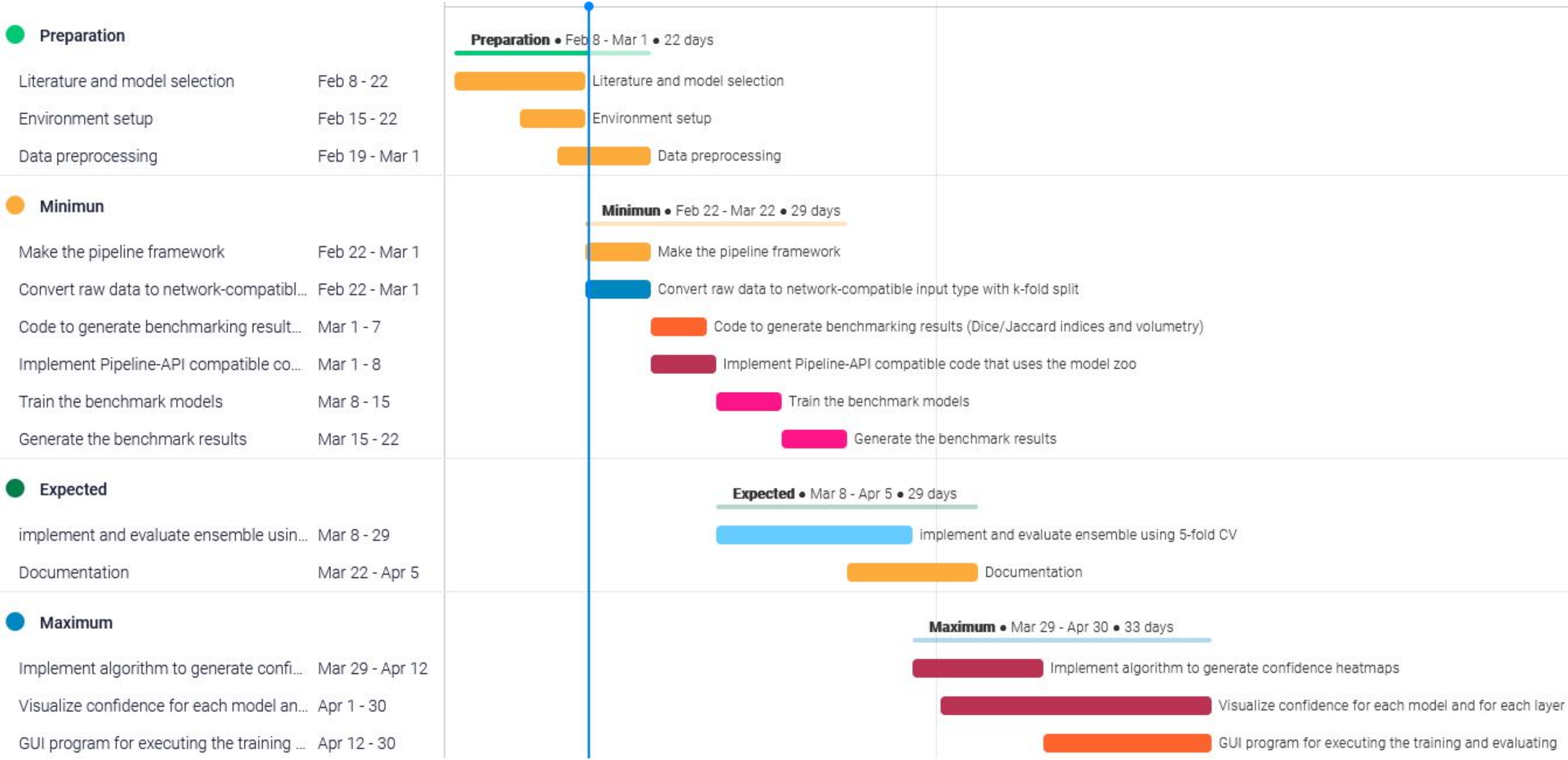
The project involves 4 majors steps.

- First step is the design of data conversion, pipeline and I/O APIs, as well as the result evaluation algorithms, which are to be done before the mid of March.
- The second step is the three model training to get us the benchmark results, ideally in parallel.
- The third step is our ensemble training, which takes the most time of this project, planned to be done by the mid of April.

As we have 3 people, the above steps are done with parallelism, as shown in the timeline graph.

- The last step, which is for our maximum deliverables, includes a GUI and training visualization system to execute training, evaluation, and prediction.

To track the progress and manage our project, we use project management software (monday.com) to update tasks, timeline, and progress, as shown in the next slide

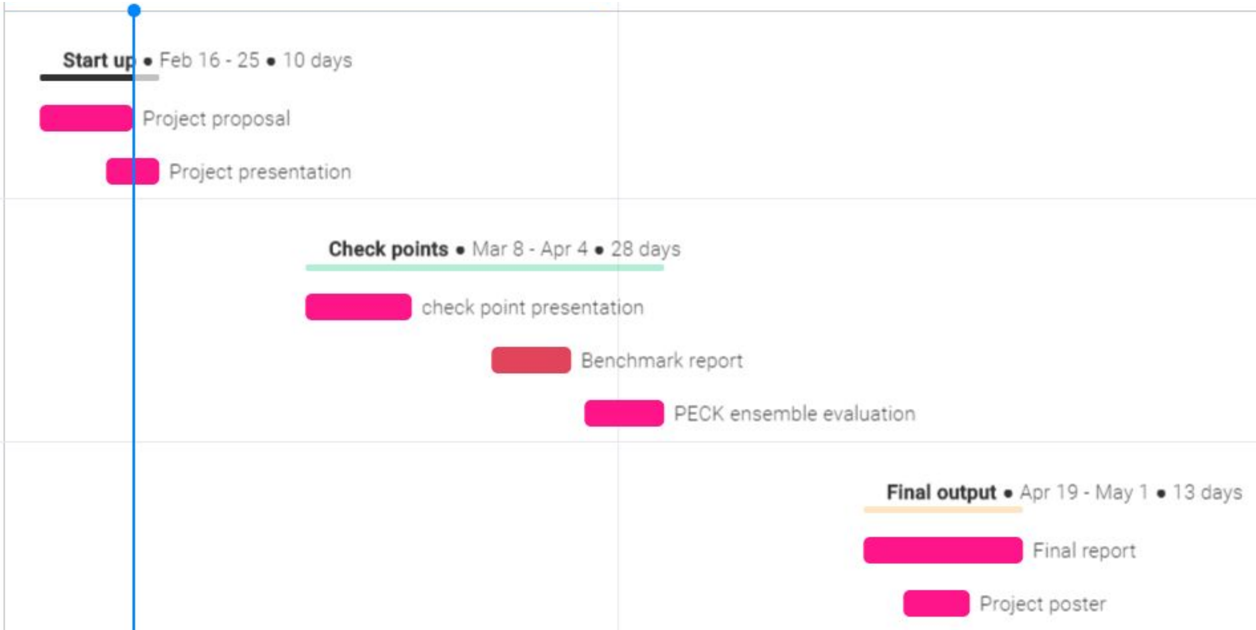


Note: Additionally, the main timeline dependency is the ensemble leading into confidence; if ensemble runs overtime, then confidence algorithm waits until ensemble is done, but visualization proceeds development

Timeline – Documentations

The documentations of our API and programs are done along the implementation and testing processes. Aside from those, our major write-ups are: this project proposal, checkpoint report, benchmark report, ensemble evaluation, poster and final report. The planned timelines for those documentations are shown below.

Start up	
Project proposal	Feb 16 - 23
Project presentation	Feb 21 - 25
Check points	
check point presentation	Mar 8 - 16
Benchmark report	Mar 22 - 28
PECK ensemble evaluation	Mar 29 - Apr 4
Final output	
Final report	Apr 19 - May 1
Project poster	Apr 22 - 27



Roles and Responsibility

a) **Team members**

- Benjamin Albert
  Undergraduate Junior, BME & CS major, responsible for the design and implementation of the ensembles and integration with train/test API.
- Chang Yan
  Undergraduate Junior, BME & CS & CE major, responsible for the train/test API, GUI design and benchmark evaluation.
- Gary Yang
  Undergraduate Junior, BME & CS major, responsible for the train/test API design and benchmark training.

b) **Team mentors**

- Dr. David Dreizin
  Associate Professor at the University of Maryland School of Medicine; provided clinical data
- Dr. Mathias Unberath
  Assistant Professor in the Department of Computer Science at Johns Hopkins University with affiliations to the Laboratory for Computational Sensing and Robotics.

Management Plan

a) Meetings

The student team meets with each other everyday through WeChat group. Progress is relayed to the mentors every couple of weeks via text and email.

b) Platforms

Codes: Github repository to work on our programs and APIs; private until disclosed by our mentors.

Communications: Communications are mainly done in Wechat Group, Zoom meetings, and emails.

Write-ups: We use private Google Docs to work on reports, presentations, and other write-ups collaboratively.

References

Dreizin, D., Zhou, Y., Zhang, Y., Tirada, N., & Yuille, A. L. (2020). Performance of a Deep Learning Algorithm for Automated Segmentation and Quantification of Traumatic Pelvic Hematomas on CT. Journal of digital imaging, 33(1), 243–251.

Dreizin, D., Zhou, Y., Fu, S., Wang, Y., Li, G., Champ, K., Siegel, E., Wang, Z., Chen, T., & Yuille, A. L. (2020). A Multiscale Deep Learning Method for Quantitative Visualization of Traumatic Hemoperitoneum at CT: Assessment of Feasibility and Comparison with Subjective Categorical Estimation. Radiology. Artificial intelligence, 2(6), e190220.

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