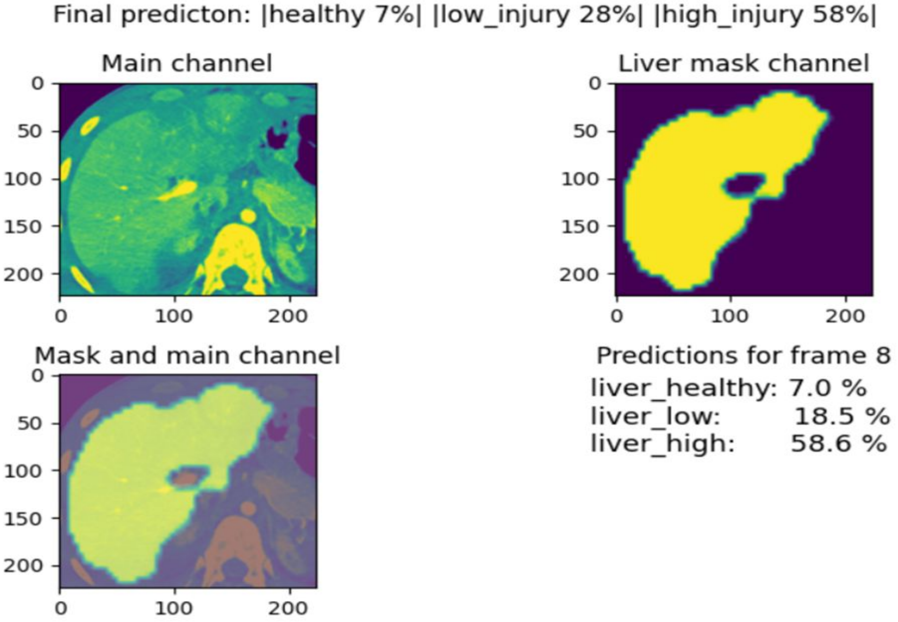
Trauma to the liver

Predicting Organ Injuries from Blunt Force Trauma using CT Scans and Machine Learning



Problem: We need faster diagnoses of organ injuries

- Trauma patients: 5.4 per 100,000 with solid organ injuries (Larsen, 2022).
- 12.5% mortality within 30 days (Larsen, 2022).
- Challenge: Identifying immediate surgery need in abdominal trauma.
- CT scans essential for detailed abdominal assessment (Errol Colak, 2023).
- Time-consuming, expert-dependent analysis.

stakeholders

Doctors and radiologists who use abdominal CT scans of patients and need to diagnose the injury status of their liver, especially when deciding if surgery is needed.

Proposed Solution

Two-stage deep learning model for organ injury prediction.

Predicts probabilities for no injury, mild injury, severe injury.

Focus on the liver, most common abdominal injury (Larsen, 2022).

Recommendations:

Triage patients with predictions.

Use bounding boxes for faster analysis.

Data

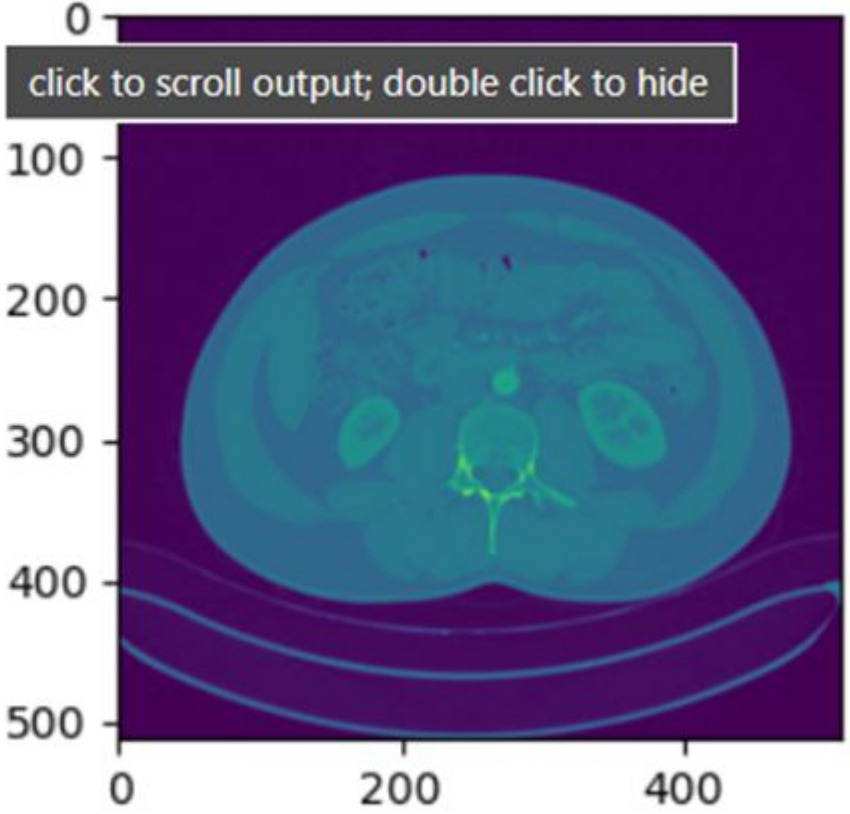
- De-identified CT scans for 3,147 patients.
- Injury labels for liver, spleen, kidney, bowels, and extravasation.
- 1564 patients with 2 scans, others with 1.
- Approximately 200 scans have segmentation masks.
- CT scans have 30 to 500 DICOM files.
- Each file: 512x512 array, tissue density in Hounsfield units (0-4000).

Data Sources:

- Curated from 23 research institutions in 14 countries (Errol Colak, et al., 2023).
- Sourced from Kaggle competition "RSNA 2023 Abdominal Trauma Detection."

Raw input

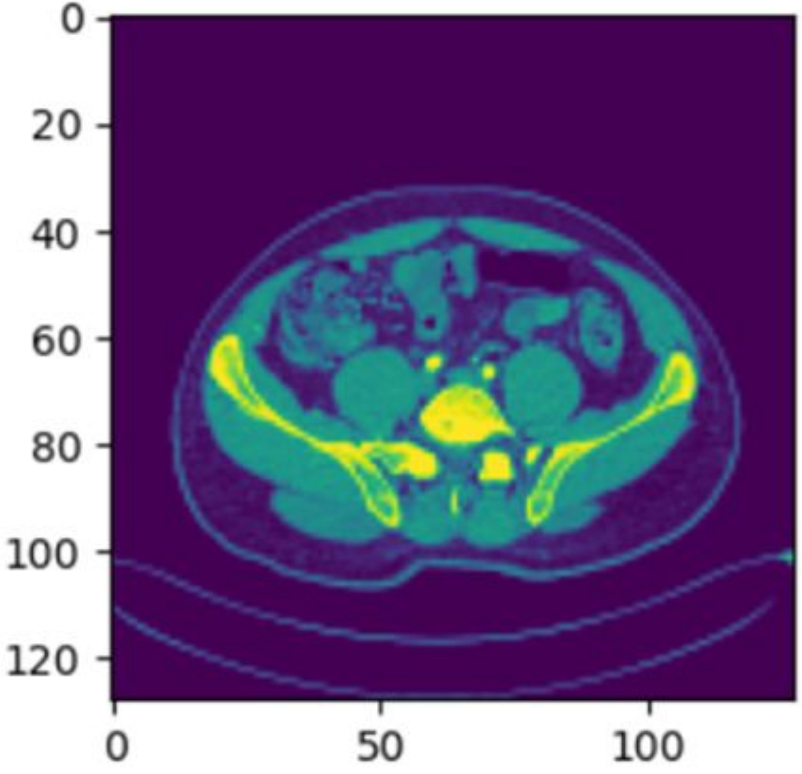
For each sample we have 30-400 dicom files containing a 512x512 single channel image



Processed input ready for segmentation (just one slice in image)

For the segmentation model, we perform the following preprocessing steps:

1. **We ensure that the images are ordered by the z-coordinate in ascending order.**
2. **Then, we resize the 3D image to a uniform size of 128x128x128.**
3. **We also clip all values to be within the radiologist annotated window of relevant values. This way we can see the structures better**

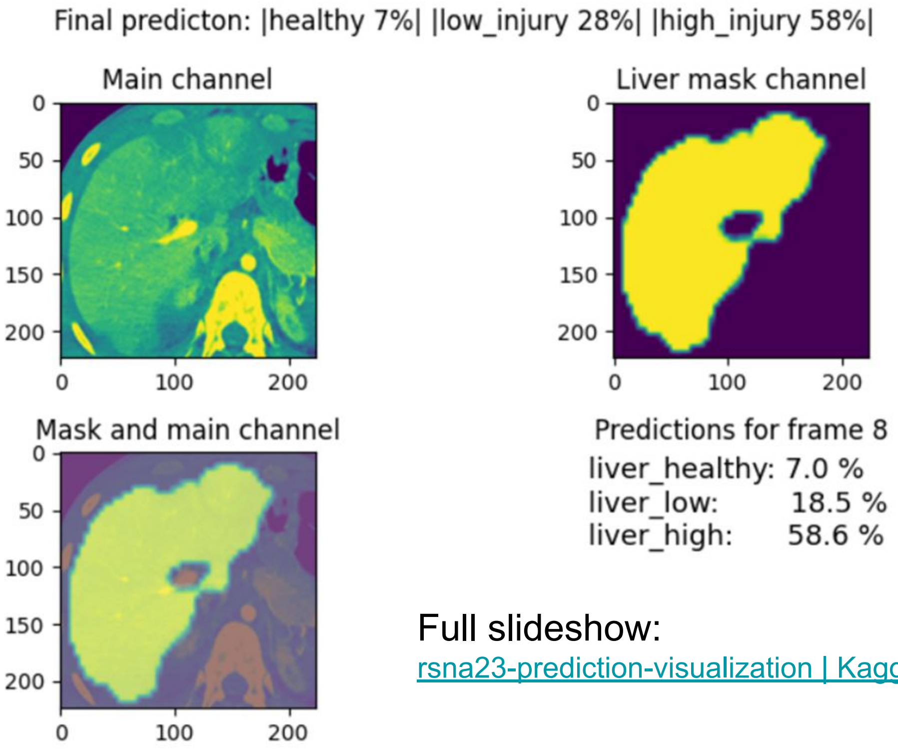


Segmentation model output -> Classifier input

Segmentation model output: Liver mask.

- Identify bounding cube around liver.
- Select 15 evenly spaced slices.
- For each slice:
- Take current image and two preceding/following.
- Create image with 6 channels (slice + 5 predicted masks).
- Input to model: 15 images, each with 6 channels.

Final predictions: , we take the min across the healthy predictions and the max across the two injury predictions.



Full slideshow:
rsna23-prediction-visualization | Kaggle

Segmentation model description

ınput: 128x128x128 3D image

Output: 5x128x128x128 tensor. 5 masks for liver, kidney, spleen, left kidney, right kidney

Architecture: Encoder/Decoder segmentation model.

- Encoder: Timm model with resnet18 backbone to get global features
- Segmentation decoder: Takes global features and upsamples to create segmentation output
- Segmentation head: takes the features from the decoder and outputs the masks

This model is also converted from a 2-D to a 3-D segmentation model.

Stage 2 classification model description

Input: 6 x 224 x 224

Output: 1 x 3 probabilities

Architecture: Encoder – LSTM – Sequential head

- Timm encoder with efficient_net backbone to extract features
- 2 Layer bi-directional LSTM
- Sequential head: 2 linear layers with batchnorm and dropout

Model experiments

<u>Model | Metric scores</u>

Baseline: .336

Base + remove mixup: .356

Base + remove distortion: .355

Base with backbone tf_efficientnet_b4_ns_jft_in1: .321

Base with backbone tf_efficientnet_b5_ap: .3177

Test set score: .3176 with model ” Base with backbone tf_efficientnet_b5_ap”

References

Errol Colak, Hui-Ming Lin, Robyn Ball, Melissa Davis, Adam Flanders, Sabeena Jalal, Kirti Magudia, Brett Marinelli, Savvas Nicolaou, Luciano Prevedello, Jeff Rudie, George Shih, Maryam Vazirabad, John Mongan. (2023). RSNA 2023 Abdominal Trauma Detection. Kaggle. https://kaggle.com/competitions/rsna-2023-abdominal-trauma-detection

Larsen, J. W., Søreide, K., Søreide, J. A., Tjosevik, K., Kvaløy, J. T., & Thorsen, K. (2022). Epidemiology of abdominal trauma: An age- and sex-adjusted incidence analysis with mortality patterns. *Injury, 53*(10), 3130–3138. https://doi.org/10.1016/j.injury.2022.06.020