Abdominal trauma detection

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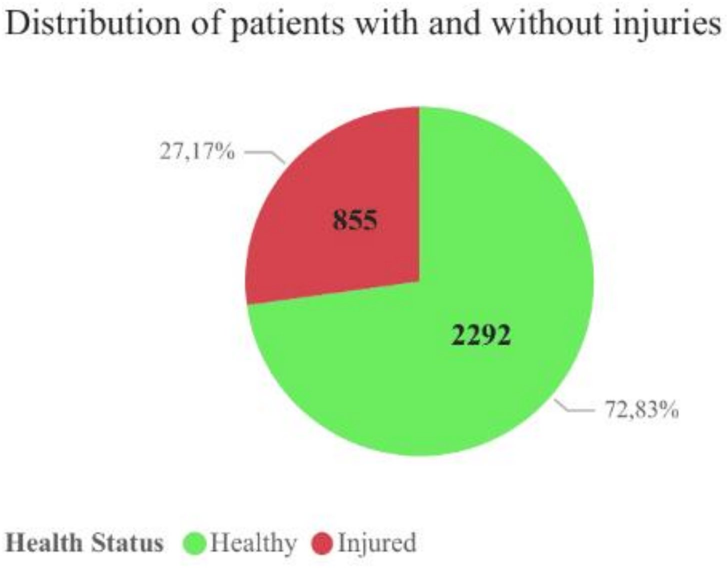
Abdominal Trauma Detection:

Problem statement:

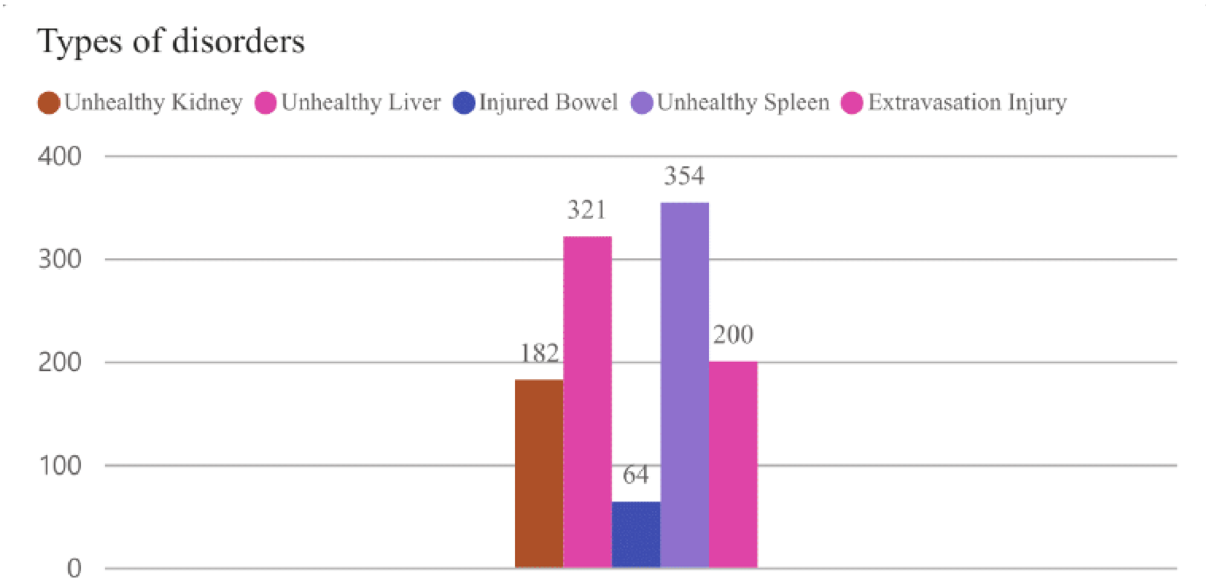
The RSNA Abdominal Trauma Detection AI Challenge aims to improve the rapid and accurate diagnosis of traumatic abdominal injuries, a major global health concern. Trauma is a leading cause of death among young individuals, with over 5 million annual global deaths. Computed tomography (CT) scans play a pivotal role in evaluating abdominal injuries, but interpretation can be intricate, particularly when multiple injuries or subtle bleeding are involved. This challenge calls for the development of AI algorithms to assist medical professionals in swiftly and precisely identifying and grading abdominal injuries, potentially revolutionizing trauma care and patient outcomes. The competition focuses on detecting injuries in the liver, spleen, kidneys, and bowel, and identifying active internal bleeding, using weighted log loss as the evaluation metric.

EXPLORATORY DATA ANALYSIS:

Based on the dataset, it's apparent that among all the patients, 2292 of them are classified as being in good health, while 855 are documented to have sustained some form of injury. This indicates a noteworthy proportion, roughly 27%, signifying a significant incidence of injuries within the patient population.



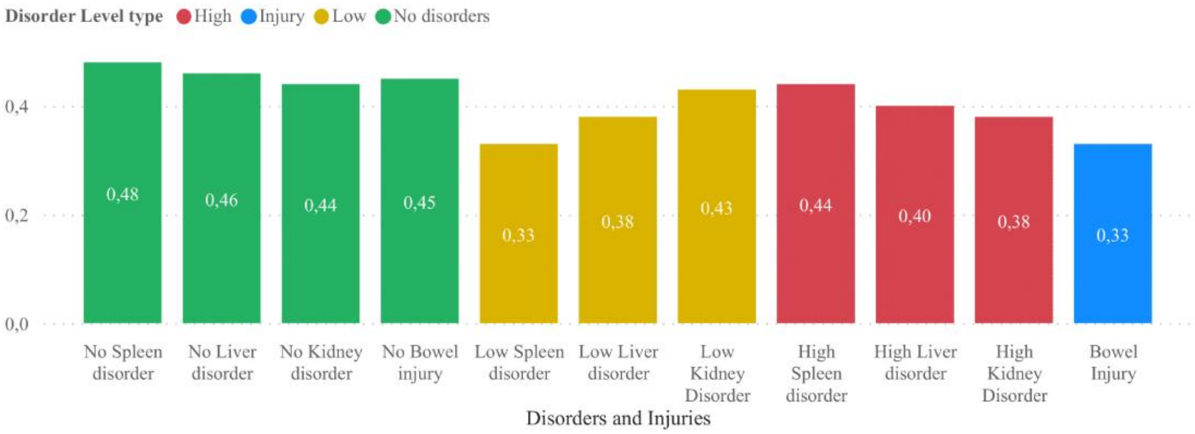
When we delve further into the specific ailments, it becomes evident that spleen disorders are the most prevalent, impacting 354 patients. Liver disorders closely follow with 321 patients affected. It's worth noting that kidney disorders affect 182 patients, and extravasation injuries impact 200 patients. In contrast, bowel injuries are the least common, with only 64 reported cases.



Exploration of Correlations:

Proportions on Injured Extravasation Combinations:

Injured Extravasation combinations	Bowel Injury	No Bowel injury	Low Kidney Disorder	High Kidney Disorder	No Kidney disorder	Low Liver disorder	High Liver disorder	No Liver disorder	Low Spleen disorder	High Spleen disorder	No Spleen disorder
24	0,33	0,45	0,43	0,38	0,44	0,38	0,40	0,46	0,33	0,44	0,48



i) When we examine the data, we notice that in cases of extravasation injuries, a greater percentage of patients do not have a bowel injury (45%) compared to those who do (33%). This finding aligns with our previous observation that bowel injuries are less common in cases of extravasation injury. It could suggest the presence of a potential protective mechanism or indicate that the factors leading to extravasation injuries don't typically affect the bowel in the same way.

ii) Regarding kidney disorders, the proportions of extravasation injuries are fairly evenly distributed, with a slightly higher occurrence in patients without a kidney disorder (44%) compared to those with a high (38%) or low (43%) level of kidney disorder. This distribution suggests that the presence of a kidney disorder may not have a substantial impact on the likelihood of an extravasation injury.

iii) Liver disorder proportions appear to be quite balanced among individuals with extravasation injuries, with a slightly higher proportion of injuries occurring in patients without a liver disorder (46%) compared to those with a high (40%) or low (38%) level of liver disorder. This implies that liver disorders, similar to kidney disorders, may not significantly influence the occurrence of extravasation injuries.

iv) However, when it comes to spleen disorders, it seems to have a more noticeable effect on the proportion of extravasation injuries. Patients without spleen disorders have a slightly higher proportion of extravasation injuries (48%) compared to those with low (33%) or high (44%) spleen disorders. This pattern suggests a potential association between the spleen's health status and the likelihood of experiencing extravasation injuries, which aligns with our previous observation regarding the co-occurrence of spleen disorders and extravasation injuries.

Summarization of analysis on Extravasation Health:

i) The examination of extravasation health in relation to the health of other abdominal organs revealed 24 unique combinations of injuries.

ii) The most frequently occurring combination was an extravasation injury without concurrent disorders in the bowel, liver, spleen, or kidney, observed in 97 patients. This suggests that extravasation injuries often occur independently of the health status of other abdominal organs. Interestingly, a significant correlation was found between high spleen disorders and extravasation injuries when no other organ injuries were present.

iii) The diversity of injury combinations is substantial, underscoring the complexity of abdominal injuries and the challenges they present in terms of accurate diagnosis and treatment.

iv) The analysis demonstrated a higher proportion of patients with extravasation injuries without bowel injuries, supporting the notion that extravasation injuries may not commonly affect bowel health.

v) The proportions of extravasation injuries were almost evenly distributed across the spectrum of kidney and liver disorders, suggesting that these conditions may not have a substantial impact on the occurrence of extravasation injuries. In contrast, spleen disorders seem to have a more significant influence on the likelihood of experiencing extravasation injuries. Further investigation is needed to determine the underlying cause of this correlation.

2 stage Pipeline:

Stage 1:

Organ Segmentation:

- In order to go from weak labels to strong labels it's important to be able to segment the organs of interest. We take an image of a patient we run a 3D segmentation model on it, it outputs masks for each slice, and we make a study-level crop here based on the boundaries of organs - liver, spleen, kidney & liver.

Data Preparation:

- You have a dataset of medical images (e.g., CT scans) and corresponding annotations (segmentations) in the form of NIFTI files. Each image may have one or more regions or structures of interest (e.g., kidney, liver, spleen, etc.).

Training Data:

- For training a segmentation model, you need images paired with accurate pixel-level annotations that specify which parts of the image belong to each structure.

- Model Architecture (TimmSegModel):

- The model used for this task is a neural network architecture specifically designed for image segmentation.
- The model has two main parts:
- Encoder: The encoder extracts features from the input image.
- Decoder: The decoder generates pixel-level predictions based on the extracted features.

Training the Model:

- During training, the model learns to map input images to pixel-level predictions (segmentations) that match the provided annotations.The model's parameters are adjusted through backpropagation to minimize the difference between its predictions and the ground truth segmentations.

Multi-Class Segmentation:

- Now our model can handle multiple structures or organs by using a "multi-class" approach. In this case, each class corresponds to a different structure (e.g., kidney, liver, etc.). The model learns to classify each pixel into one of these classes, resulting in a multi-class segmentation map.

Inference:

- After training, you can use the model to perform inference on new, unlabeled medical images. The model takes an input image and produces a segmentation map that highlights the different structures within the image.

Second Stage:

Organ Injury Classification with RESNET-18 + LSTM (RNNs)

LSTM in Medical Imaging:

- The Long Short-Term Memory (LSTM) layer acts as an intelligent filter for sequences of data, like a series of images taken over time.
- In medical imaging, sequences of 2D images (slices) captured over time are common. Each image represents a different cross-section of the 3D volume within a patient's body.
- The LSTM layer plays the role of a detective, retaining vital information from one slice to the next. It excels in identifying patterns or changes in the images as you progress from one slice to another.

Pipeline Components:

- ResNet-18 Feature Extractor: We employ a ResNet-18 model as a feature extractor. ResNet-18 is a well-established convolutional neural network (CNN) architecture, renowned for its capability to capture essential image features. In our application, it serves to extract vital information from medical images.

- Organ-Specific LSTM Models: After the medical images pass through the ResNet-18 backbone, we thoughtfully integrate individual LSTM models into the pipeline. Each LSTM model is dedicated to a specific organ. These Long Short-Term Memory (LSTM) models, a type of recurrent neural network (RNN), are meticulously designed to handle sequential data. In our medical imaging context, they play a pivotal role in capturing temporal dependencies across slices within the 3D volume for each organ.

- Organ-Specific Classification Layers: In alignment with the LSTM models, we introduce separate classification layers for each organ. These layers are finely tuned to provide distinct predictions for various injury types within each organ. In our code, we structure them to generate predictions for 11 different classes, each representing specific medical conditions or injury types.

This organizational approach ensures precise injury classification tailored to each organ, enhancing the overall effectiveness of the model.

Creating a 3D Volume from 2D Slices:

- Ordering by 'instance_id': The 2D image slices, referred to as instances, undergo meticulous sorting based on their 'instance_id'. This vital step guarantees that the slices are in the correct sequence for subsequent processing.
- Implementing Image Processing: The code capitalizes on a read_dicom_image function, applying it to each instance within the sorted instances through the apply method. This function's role encompasses reading and processing individual DICOM images, including the extraction of pixel values and the application of specific transformations.
- Constructing a 3D Array: The processed images, derived from the instances, are conscientiously aggregated into a 3D array using np.stack. This critical step effectively compiles the 2D slices into a cohesive 3D volume, which faithfully represents the complete

image or scan. Each 2D slice contributes to the formation of this comprehensive 3D image.

- Conversion to a PyTorch Tensor: The resultant 3D array of images is subsequently transformed into a PyTorch tensor using the torch.Tensor method. This pivotal conversion ensures that the data is appropriately structured for further processing and analysis by deep learning models.

Result Analysis:

Overall Weighted log loss :0.66

Results:

results before and after implementing separate lstm models for each organ:

Accuracy	Before Implementation	After Implementation
Bowel injury	0.74	0.89
Extravasation injury	0.77	0.84
Liver injury	0.85	0.88
Spleen injury	0.80	0.87
Kidney injury	0.76	0.83

Precision	Before Implementation	After Implementation

Bowel injury	0.75	0.86
Extravasation injury	0.74	0.90
Liver injury	0.83	0.89
Spleen injury	0.74	0.82
Kidney injury	0.69	0.85

F1-Score	Before Implementation	After Implementation
Bowel injury	0.73	0.85
Extravasation injury	0.76	0.83
Liver injury	0.82	0.88
Spleen injury	0.77	0.84
Kidney injury	0.71	0.82

Future Directions:

While our results show promising accuracy improvements, further research should explore additional factors, including hyperparameter tuning, ensembling techniques, and more extensive datasets to enhance the model's generalization capabilities.