ABDOMINAL TRAUMA CLASSIFICATION AND SEVERITY PREDICTION

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Project Overview

- ❖Project Objective: Address the critical issue of prompt and accurate diagnosis of abdominal trauma.
- ❖Significance: Abdominal trauma is a common cause of death and a major global public health concern.
- ❖Causes: Often results from motor vehicle accidents.
- ❖Consequences: Can lead to severe injuries to internal organs and internal bleeding.

Problem Statement

- ❖ Over 5 million people worldwide succumb to traumatic injuries annually, creating a severe public health crisis.
- ❖ Blunt abdominal trauma from car accidents often leads to internal bleeding and severe damage.
- ❖ Kenya, with a population of over 50 million, faces significant healthcare system issues.
- ❖ Only 200 trained radiologists and approximately 50 CT scanners exist across the entire state, resulting in:
  - Frequent False Positives
  - Extended Wait Times (often weeks)
- ❖ A considerable portion of the Kenyan population lacks access to essential healthcare services.
- ❖ The urgency for swift and accurate diagnosis persists, despite government efforts to increase CT scanners and train more radiologists.

Objectives

- ❖ To develop AI algorithms that can automatically and accurately detect traumatic injuries to internal abdominal organs using CT scans.

- ❖ To classify the discovered injuries according to their severity, thereby providing medical experts a vital tool to start proper treatment.

- ❖ To rigorously evaluate the developed algorithms using performance metrics that are relevant for both machine learning models and clinical applicability.

Research Questions

- How effective are AI algorithms in automatically detecting traumatic injuries to internal abdominal organs like the liver, kidneys, spleen, and bowel using CT scans?
- What features and patterns in CT scans are most indicative of different severities of abdominal injuries, and how can they be utilized for automated injury grading?
- What are the appropriate metrics for evaluating the performance of the developed AI algorithms in terms of both machine learning benchmarks and clinical utility?

Data Understanding

1. labels (image_level_labels.csv) Dataset:

- •Rows: 12,029
- •Columns: 4
- •Columns include patient_id, series_id, instance_number, and injury_name.
- •Data Types: Integer types for identifiers and string for injury names.
- •Unique Values: 246 unique patients, 330 unique series, 925 unique instances, 2 unique injury types (Active_Extravasation and bowel).

2. train (train.csv) Dataset:

- •Rows: 3,147
- •Columns: 15
- •Columns include patient_id, 'any_injury', and 13 binary variables for organ health and injury presence.
- •Data Types: All columns are integers.
- •Unique Values: 3,147 unique patients, binary injury-related columns.

3. train_meta (train_series_meta.csv) Dataset:

- •Rows: 4,711
- •Columns: 4
- •Columns include patient_id, series_id, aortic_hu, and incomplete_organ.
- •Data Types: Integer and float types.
- •Unique Values: 3,147 unique patients, 4,711 unique series, binary incomplete organ feature.

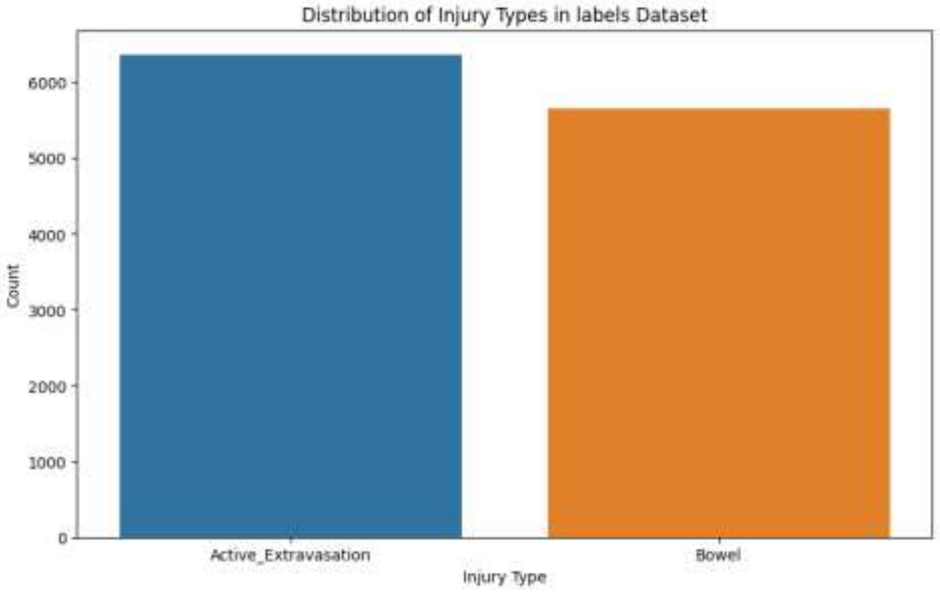
Data Understanding

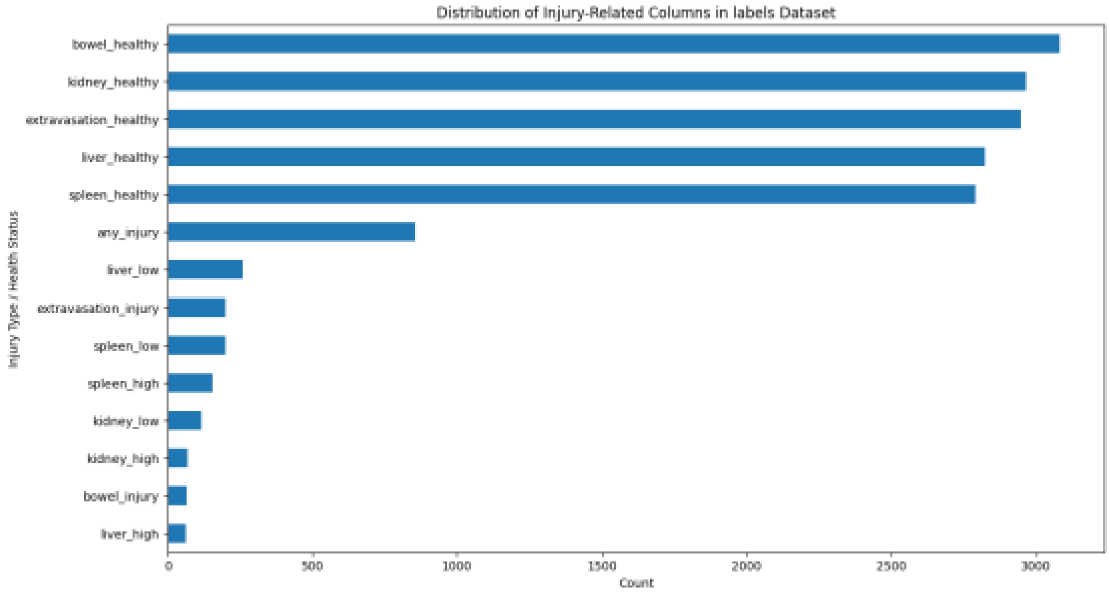
- **Statistical Summary - Train Dataset**
- **Patient IDs Distribution:**
  - Wide range of patient IDs, from 19 to 65,508.
- **Organ Health Status:**
  - Binary indicators of organ health.
  - Most patients have healthy organs (mean values close to 1).
- **Organ Injury Severity:**
  - Binary indicators of injury severity.
  - Low mean values, indicating rare severe injuries.
- **Overall Injury Presence:**
  - 'any_injury' column indicates the presence of any injury.
  - Approximately 27% of patients have at least one injury.

Data Understanding

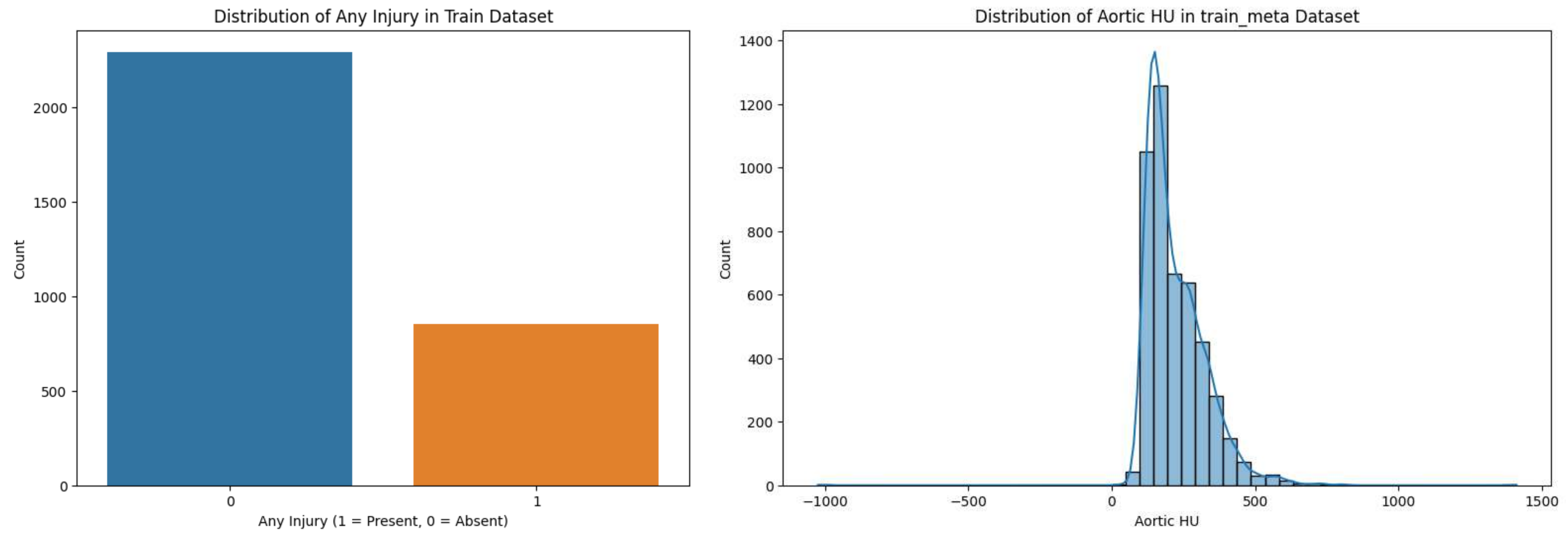
- **Statistical Summary - Train_Meta Dataset**
- **Aortic Hounsfield Units (HU):**
  - Mean HU value: ~223.62, indicating moderate density.
  - Significant HU value spread (std. dev. ~103.77).
  - Outliers with min -1024 and max 1411.
- **Incomplete Organ:**
  - Mean value: ~0.066, suggesting rare presence.
  - Some variability (std. dev. ~0.249).

Univariate EDA



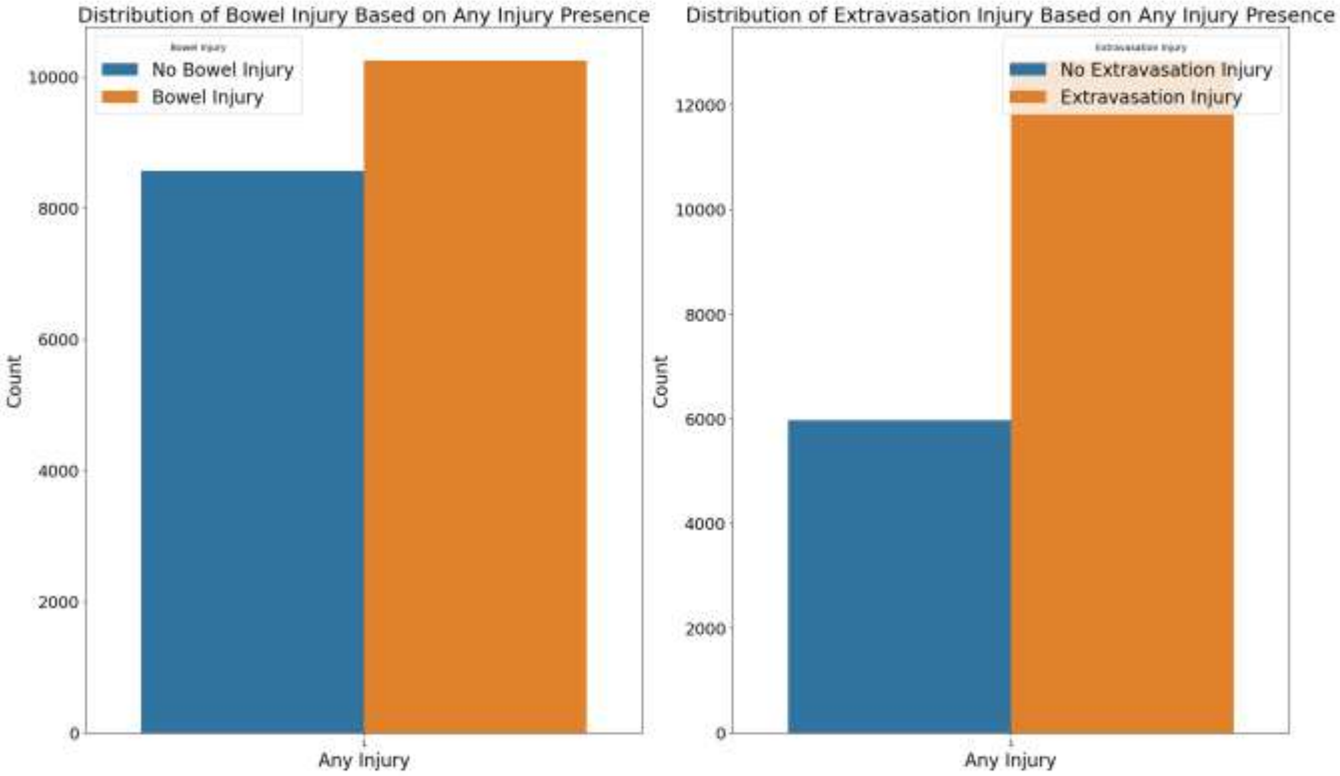


Univariate EDA

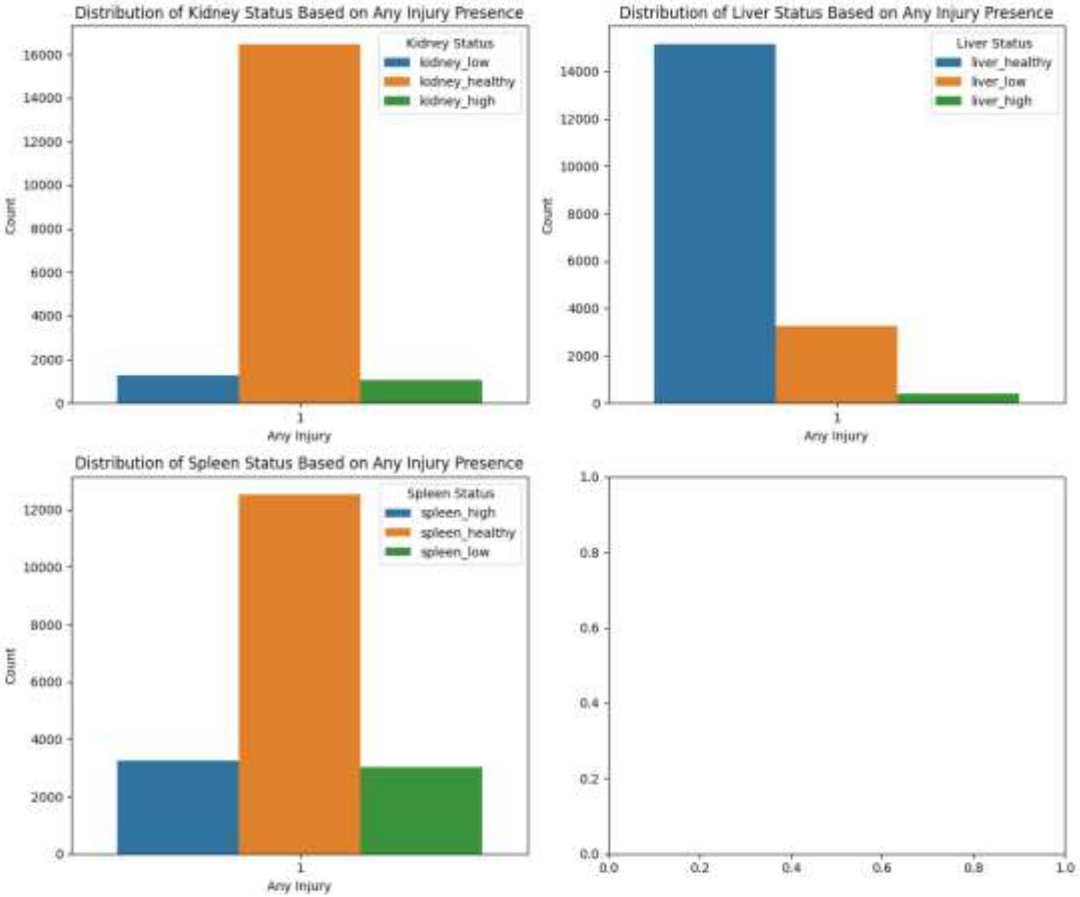


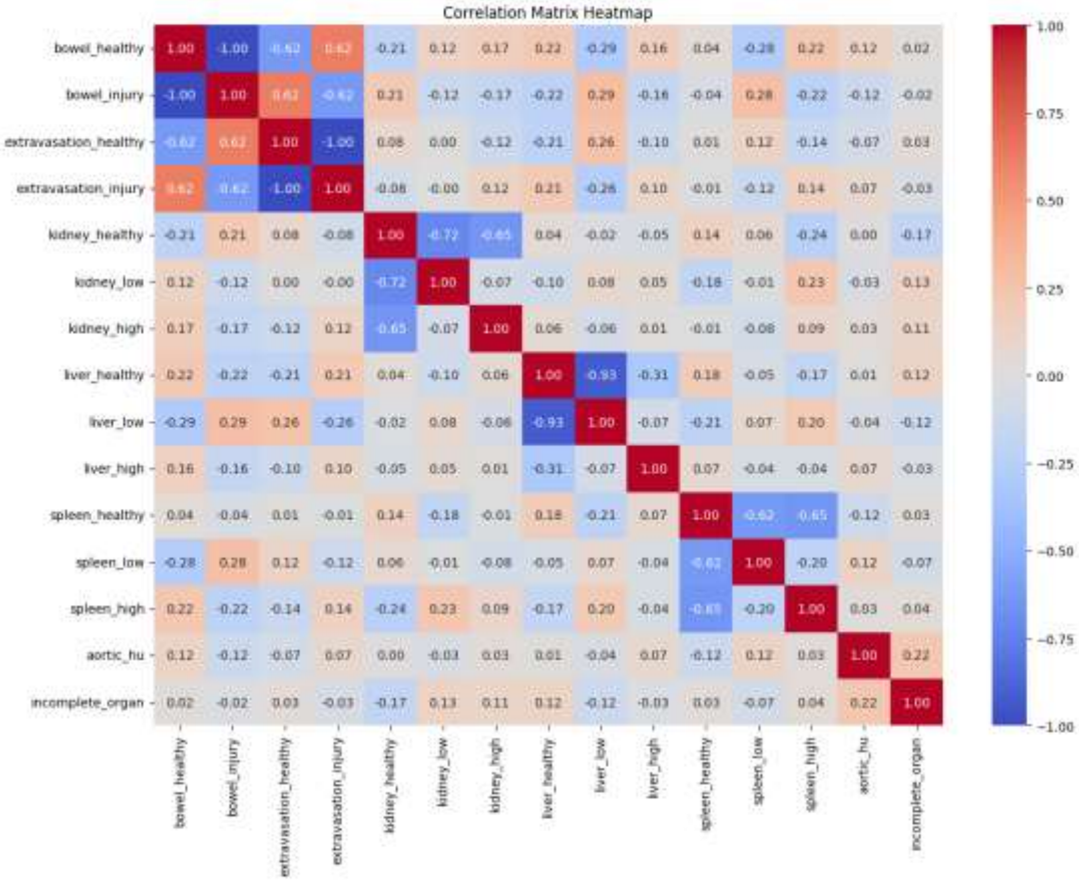
Bivariate EDA

- We used a grouped bar chart to compare 'Bowel Injury' and 'Extravasation Injury' based on the presence or absence of any injury.
- n cases with any injury ('any_injury=1'), 'Bowel Injury' is slightly more prevalent compared to cases without injury.
- in cases with any injury, 'Extravasation Injury' is significantly more prevalent than cases without injury

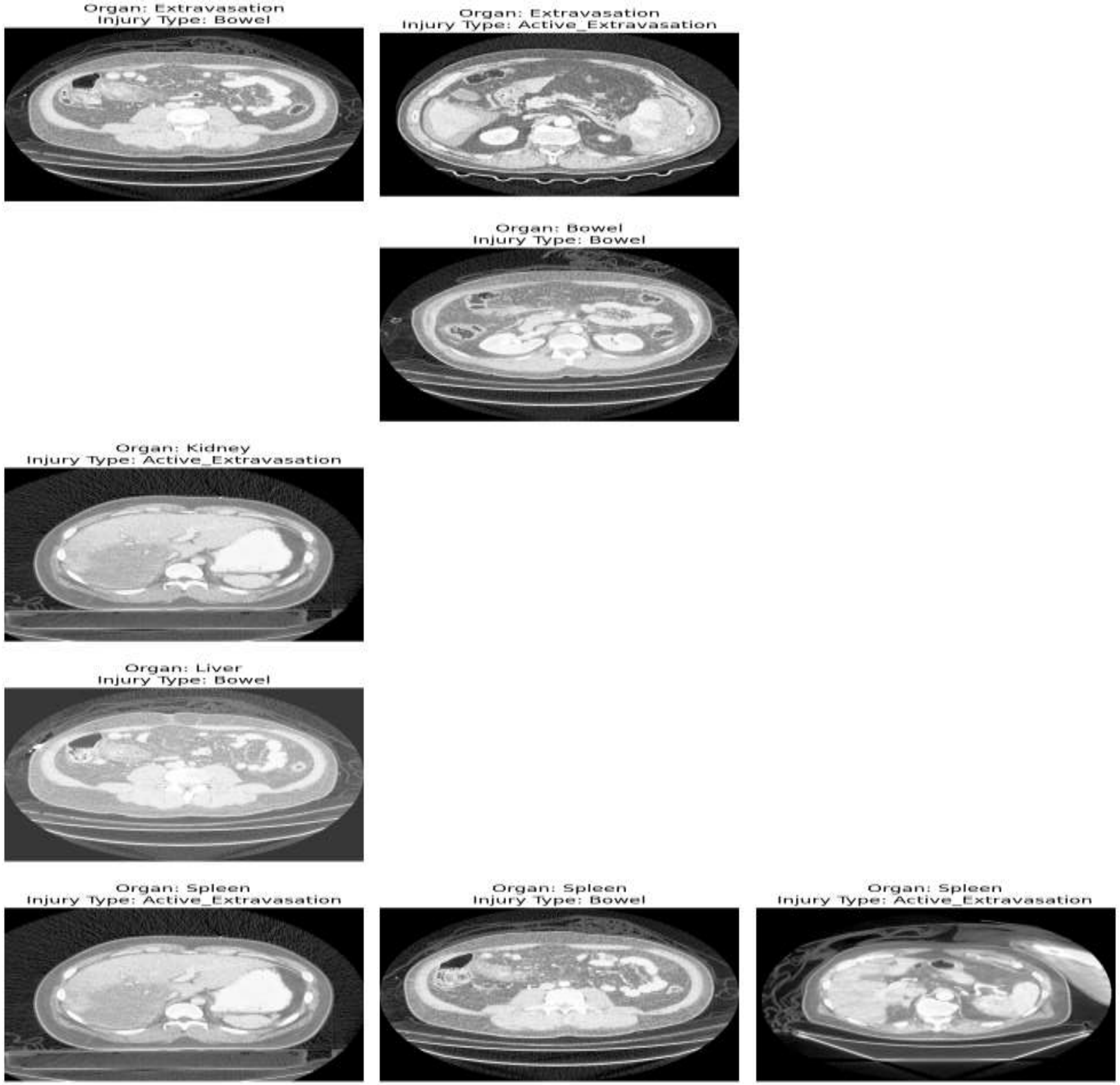


Bivariate EDA





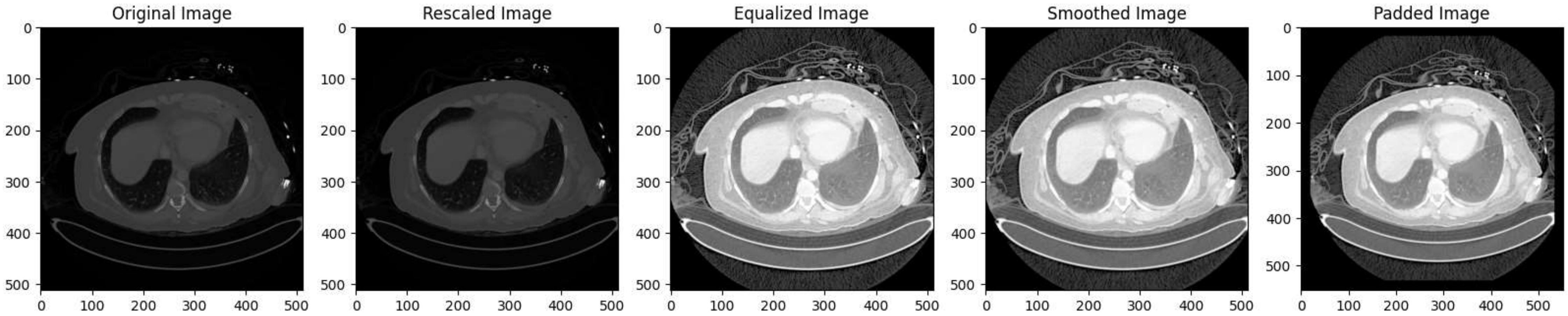
Images: Healthy and Injured Abdominal Organs Comparison



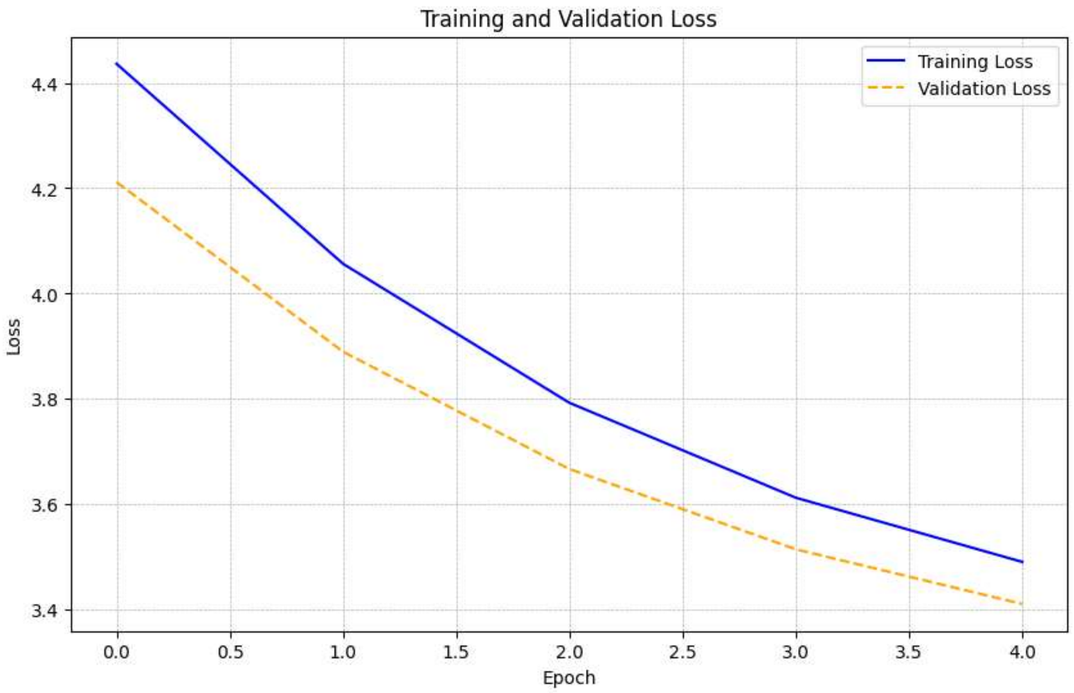
The image shows healthy and injured organs for 5 different patients

Image Preprocessing

Data preprocessing involved rescaling, equalizing, smoothing and padding the images



Modelling



Our 3rd model was the best performing:
Total Loss: 3.4111
75/75 accuracy overall, indicating all test cases were correctly classified.
Individual Losses for Organ Classes:
Bowel: 0.6918
Extra: 0.6408
Liver: 0.5498
Kidney: 0.6477
Spleen: 0.8810
Organ-Specific Metrics:
Bowel:
Accuracy: 0.5275
Precision: 0.5304
Extra:
Accuracy: 0.6927
Precision: 0.6946
Liver:
Accuracy: 0.8813
Precision: 0.8821
Kidney:
Accuracy: 0.8147
Precision: 0.8158
Spleen:
Accuracy: 0.6830
Precision: 0.6850

Conclusion

Bowel and extravasation injuries are more common in the presence of any abdominal injury, aiding targeted assessments by medical professionals.

Liver injuries vary in severity, with low severity being prominent, guiding classification and treatment priority.

Rare cases of incomplete organs highlight the need for accurate injury diagnosis in compromised organ visibility.

Interactions between injury types and organ statuses are revealed, directing the model's focus.

Subtle hyperdensity differences indicate injury severity, emphasizing advanced image processing techniques.

Spleen injury detection remains a significant challenge, requiring specific approaches.

Understanding complex Aortic Hounsfield Unit distributions is essential for injury severity assessment.

Addressing class imbalance improves model performance for various organ injuries.

Prioritizing precision reduces false positives, vital in medical contexts.

Careful tuning of the DenseNet121 architecture balances accuracy and false positives.

Model 3 with balanced accuracy, enhanced precision, and consistent performance is a reliable tool for critical medical diagnoses.

Recommendations

- Utilize knowledge of common injury combinations (e.g., bowel and extravasation injuries) for more efficient assessments.
- Collaborate with practitioners to improve models for accurate diagnosis in cases of compromised organ visibility, using additional imaging techniques or supplementary tests.
- Allocate research efforts to address challenges in spleen injury classification through algorithm experimentation and multidisciplinary approaches.
- Stay informed about the complexity of Aortic Hounsfield Units (HU) to enhance the development of more effective algorithms
- Implement techniques for explainable AI to provide transparency in model predictions, building trust with medical practitioners.