

# Improving Rib Fracture Detection in CT: Overcoming the Challenge of Non-Displaced and Buckle Fractures

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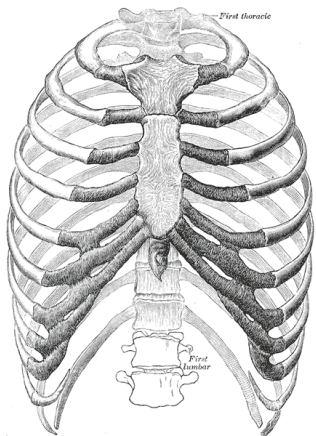


## 1. Challenges in Rib Fracture Diagnosis

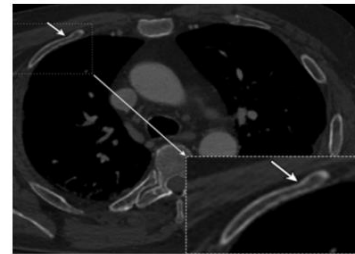
- Identifying 12 pairs of ribs in CT data is a labor-intensive task.
- Buckle fractures are the most frequently missed type of fracture.

[Ref]: Dankerl P, Seuss H, Ellmann S, Cavallaro A, Uder M, Hammon M. Evaluation of Rib fractures on a single-in-plane image reformation of the rib cage in CT examinations. Acad Radiol 2017;24(2):153–9.

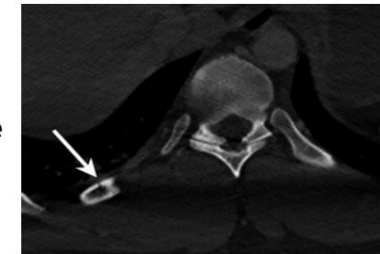
- Non-Displaced fractures are also among the hard-to-detect rib fractures.



**Buckle Rib Fracture**



**Non-displaced Rib Fracture**



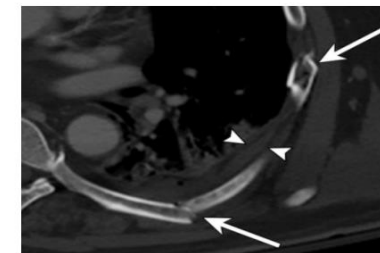
[Ref]: Henry Gray's Anatomy of  
the Human Body

[Ref]: MICCAI 2020 Rib Frac  
Challenge

**Displaced Rib Fracture**



**Segmental Rib Fracture**



### 2. Limitations of Current Diagnostic Methods

- Diagnosis using CT data involves reviewing numerous images, which is time-consuming.
- The extensive analysis of vast amounts of imaging data leads to increased fatigue among radiologists.
- Analyzing this much data can lead to fatigue accumulates, making it easy to overlook subtle findings such as buckle fractures and non-displaced fractures.

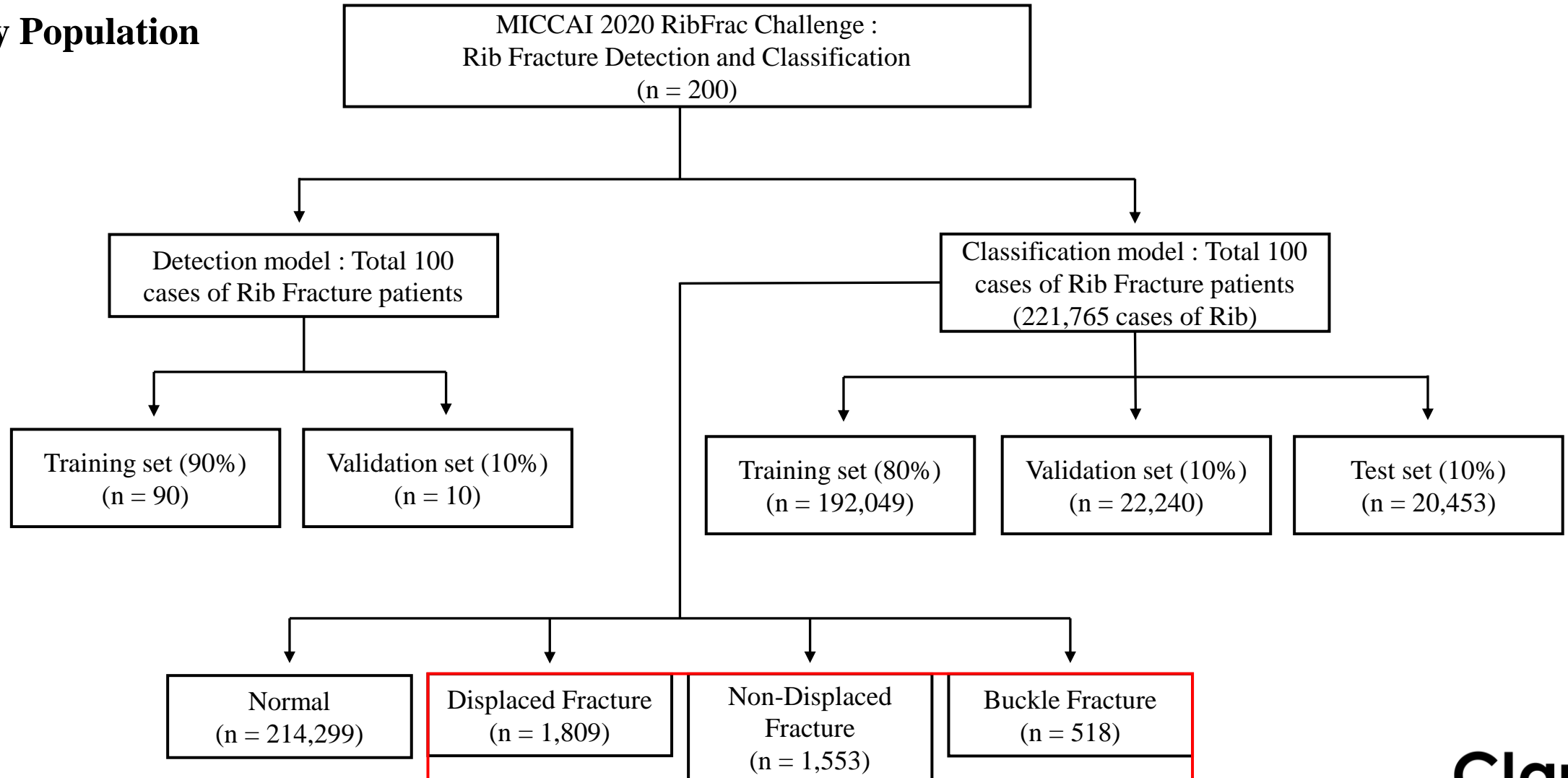
# Purpose

The 80th Korean Congress of Radiology and Annual  
Delegate Meeting of the Korean Society of Radiology

KCR2024

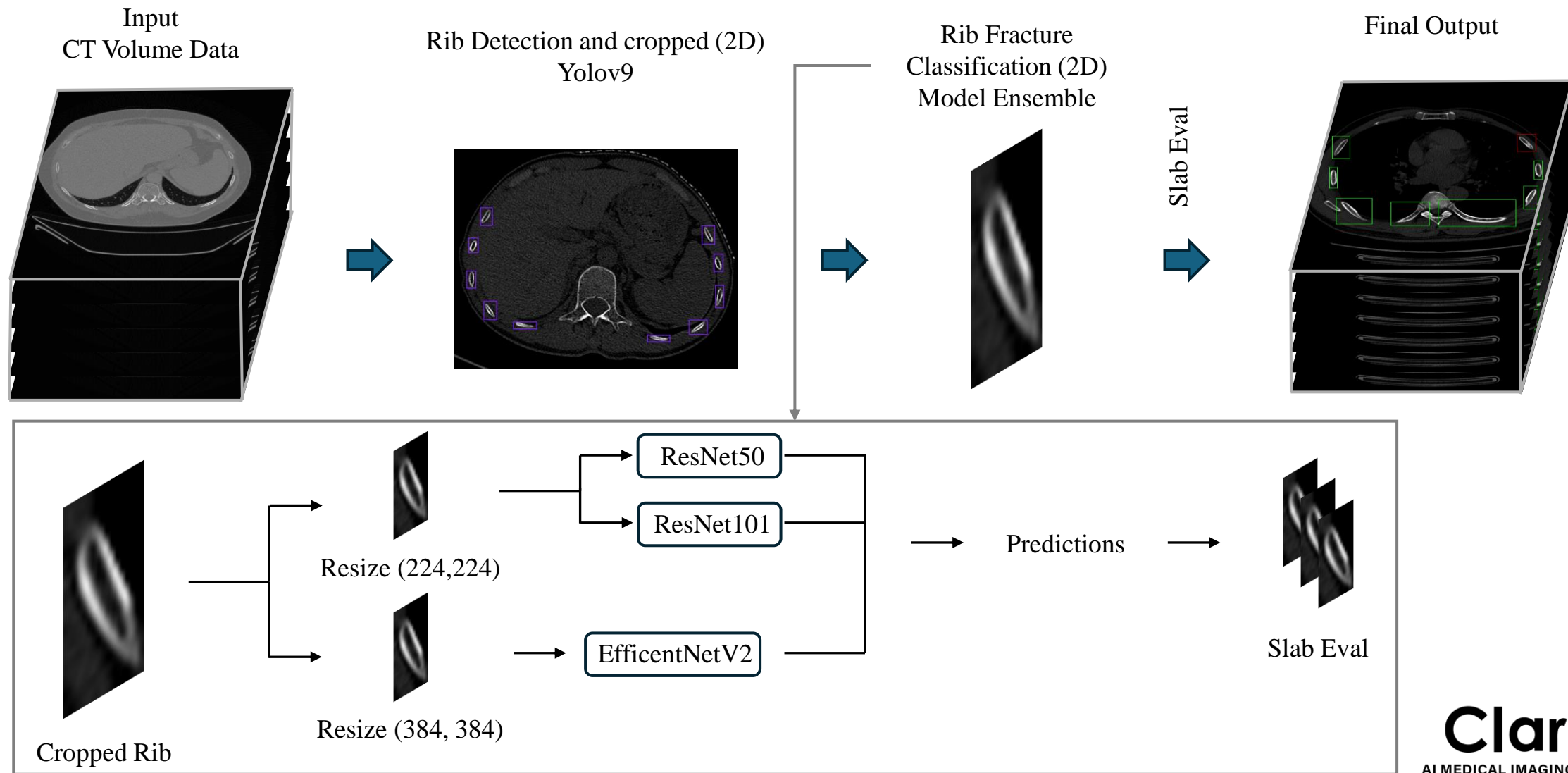
- To develop a deep learning model to automatically detect rib fractures from CT data.
- To enhance the ability to identify subtle fractures such as buckle and non-displaced fractures, which are often challenging to detect.

## Study Population

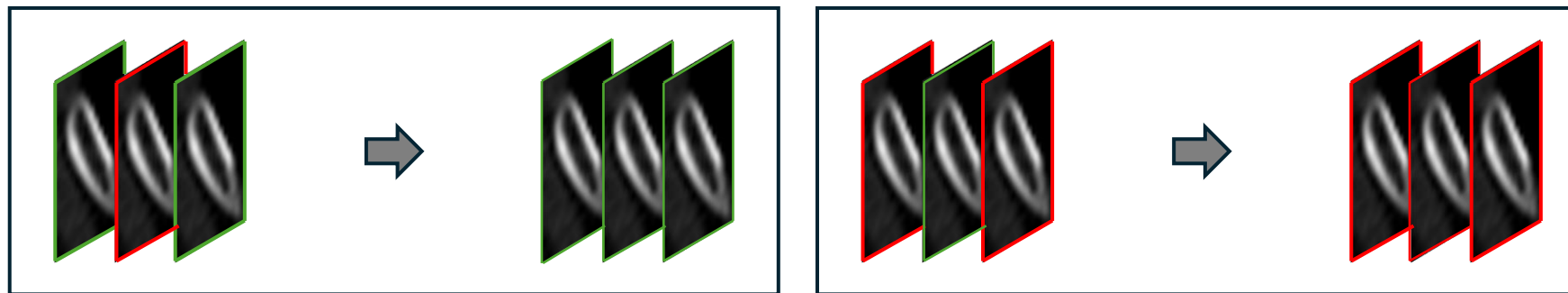




## Overview of our Rib Fracture detection framework



## Overview of our Slab Evaluation framework

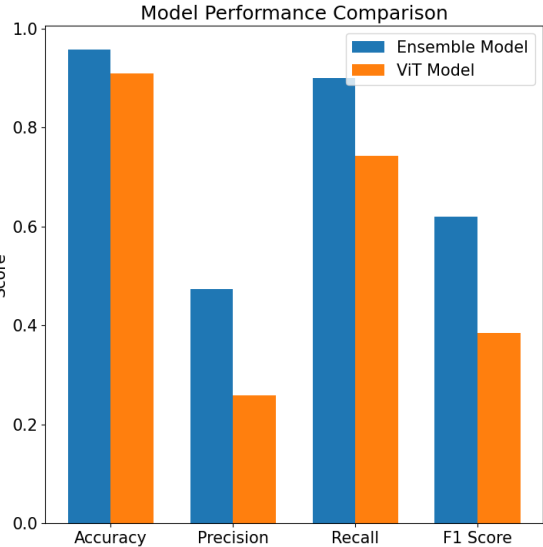
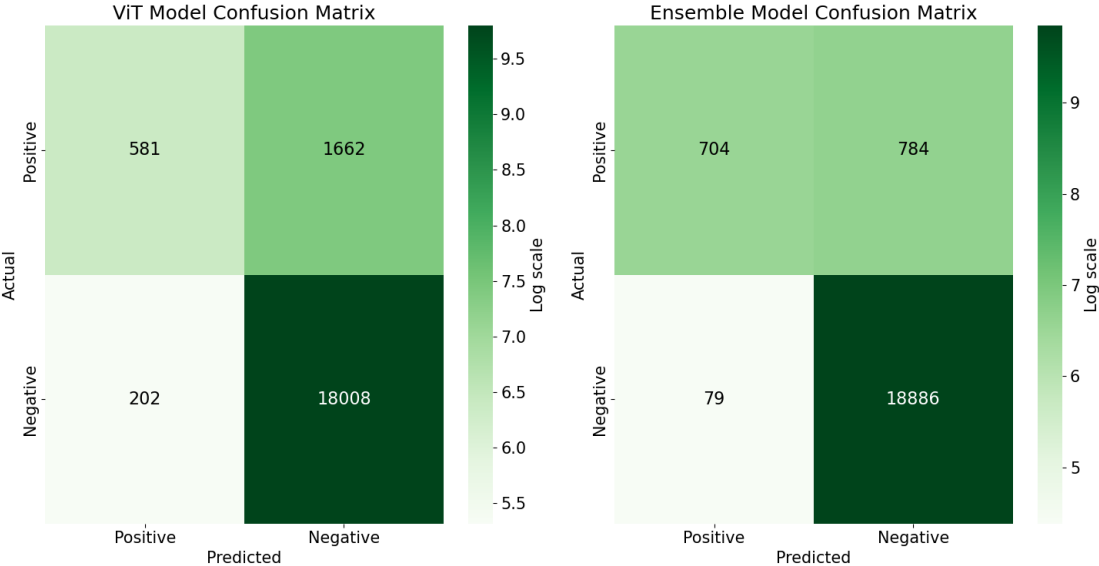


- Rib fractures typically appear continuously across multiple slices. It's uncommon for a single image to show a positive result while the adjacent slices (before and after) show negative results.
- Moreover, if both the preceding and following slices show positive results, there's a very high probability that the rib in the middle slice is also positive.

## Verification Methods

- Compared Vision Transformer (single model) and an ensemble model
  - We used the relatively new model, the Vision Transformer model, for comparison.
- Results analyzed using sensitivity, specificity and visualizations of confusion matrix, accuracy, precision, recall, and F1 score





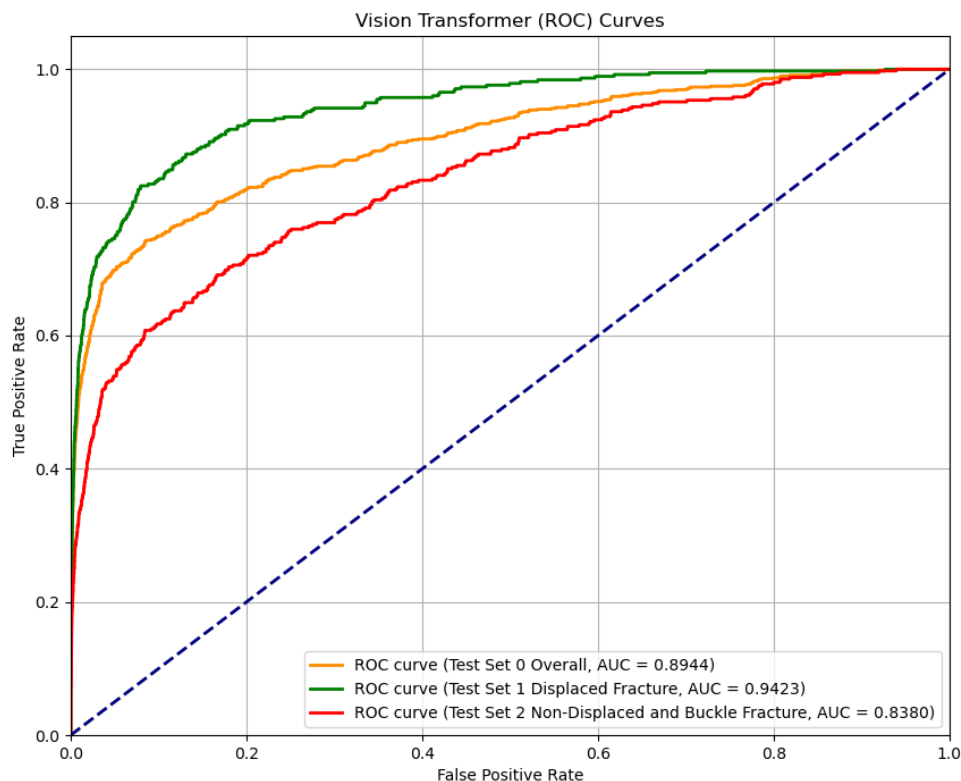
Ensemble Model Metrics:  
Accuracy: 0.9578  
Precision: 0.4731  
Recall: 0.8991  
F1 Score: 0.6200

ViT Model Metrics:  
Accuracy: 0.9089  
Precision: 0.2590  
Recall: 0.7420  
F1 Score: 0.3840

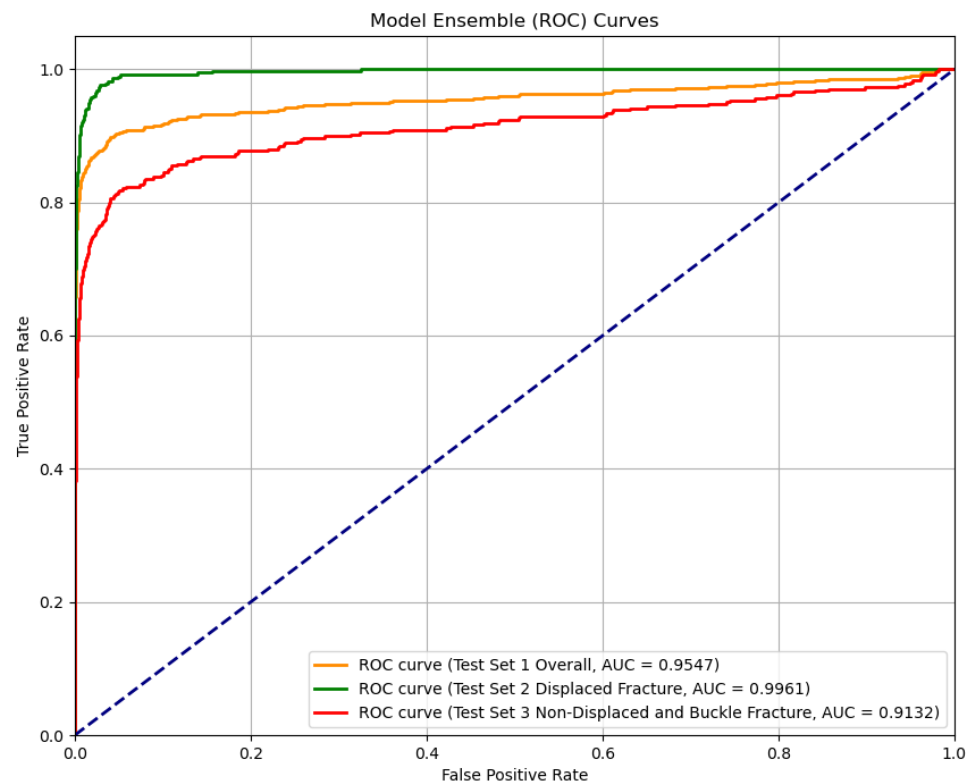
Model	Sensitivity		Specificity	
	ViT	Ensemble	ViT	Ensemble
Overall (n=783)	74.20%	89.91%	91.55%	96.01%
Displaced (n=377)	82.49%	97.61%	92.05%	97.12%
Non-Displaced and Buckle (n=408)	69.12%	81.86%	83.36%	94.93%

Table 1. Vision Transformer and Ensemble Model Results for Fracture Classification.

## ROC Curves: A Comparison of ViT and Model Ensemble

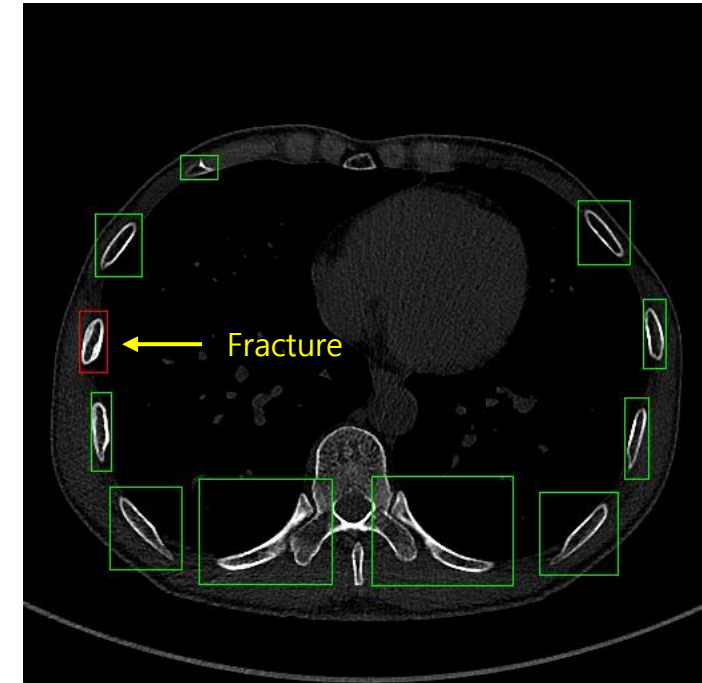
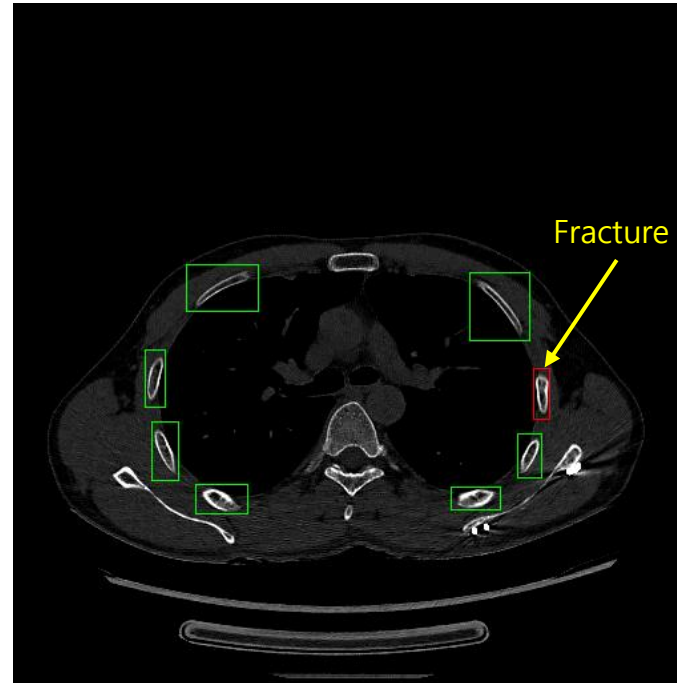
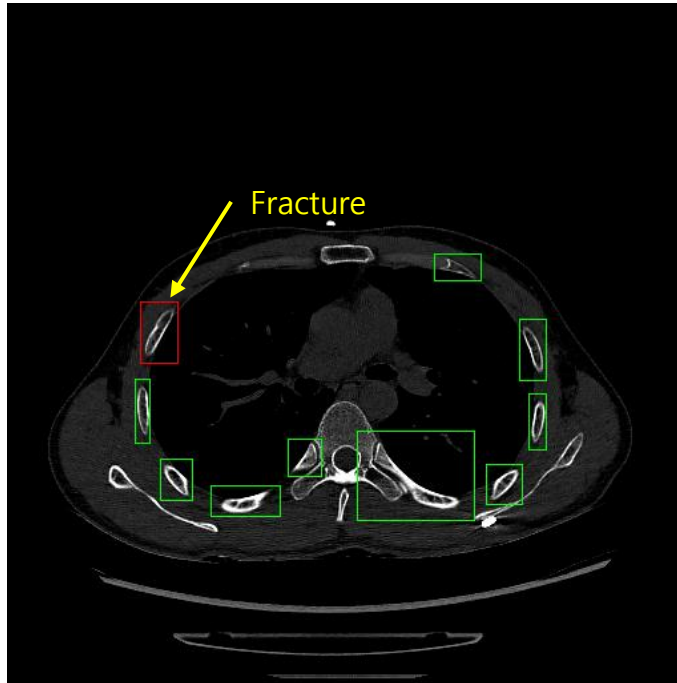


Vision Transformer (ROC) Curves



Model Ensemble (ROC) Curves

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- The current model can detect fractures but cannot specify exact anatomical locations of rib fractures.
- The dataset lacked diversity, potentially affecting the model's generalizability to a wider range of fracture types and patient demographics.

- This study employed a two-stage, approach, consisting of detection followed by classification.
- The classification model's performance was maximized through the construction of an ensemble using ResNet50, ResNet101, and EfficientNetV2.
- The ensemble model outperformed individual models in predictions.
- Future work will explore 2.5D and 3D predictions for improved performance.



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**감사합니다**  
**Thank you for your attention**

