Skull fracture detection in CT images using YOLOv5 with multi-detected gates

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Introduction

- Skull fractures, following head trauma, may bring several complications and cause epidural hematomas. Therefore, it is of great significance to locate the fracture in time.
- In this report, we compare different models and apply exploratory data analysis to determine which method is suitable for the task of skull fracture.

Methodology

A. Data pre-processing

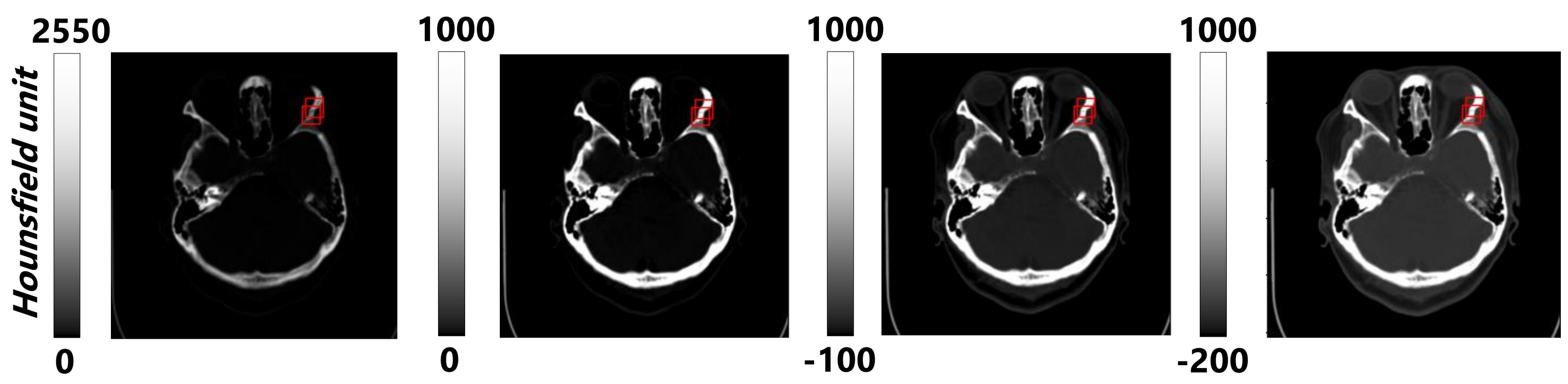


Fig 1. Data transformation under different HU ranges

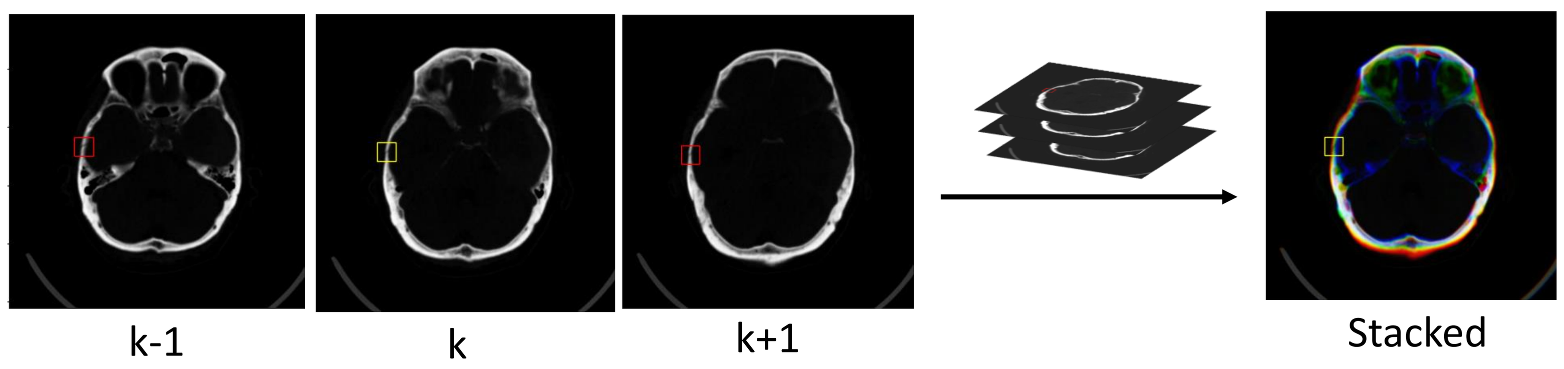
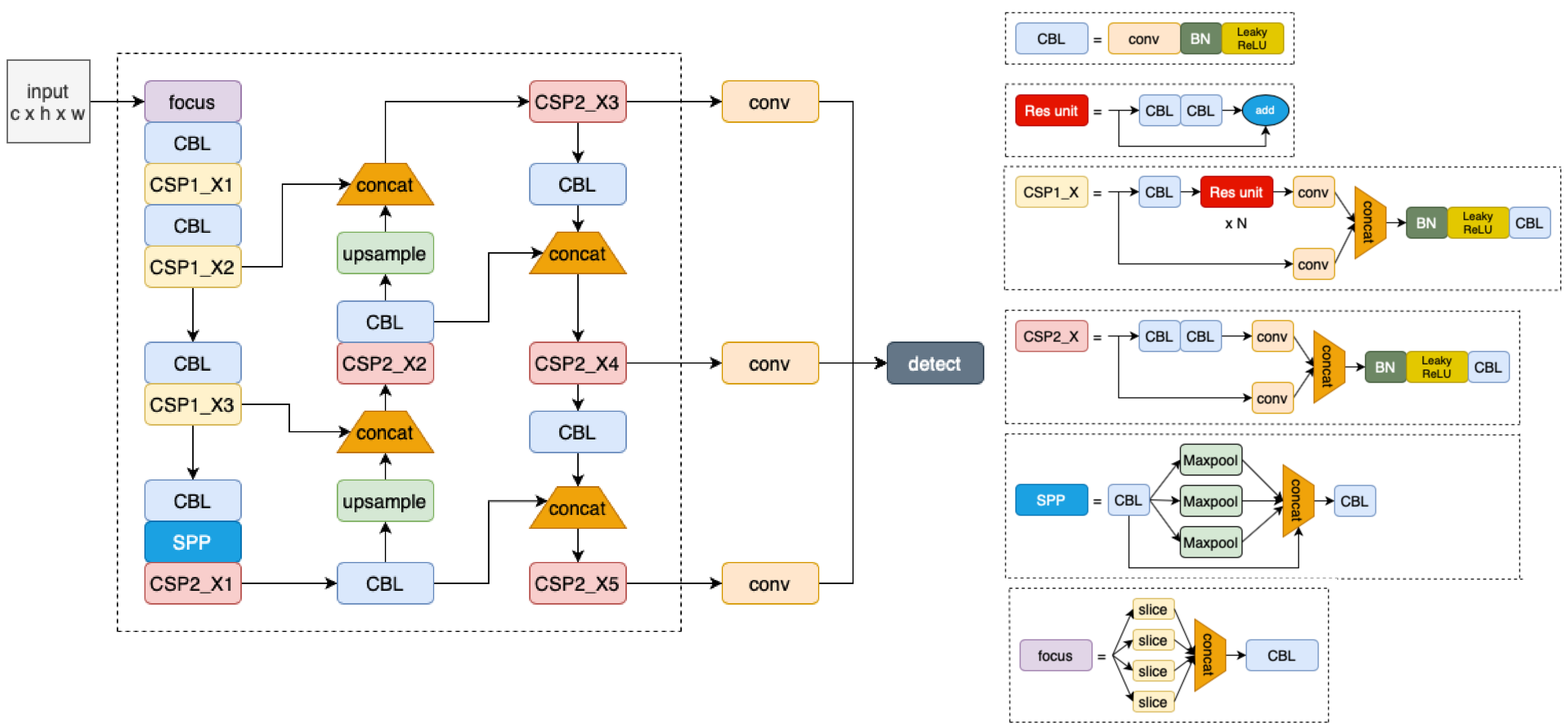


Fig 2. Stack three consecutive gray level images to form a 3-channel image

B. Model Architecture



YOLOv5 can be separated as three important parts:

- Model Backbone:
  Extract important features from a given input image.
- Model Neck:
  Generate feature pyramids.
- Model Head:
  Apply anchor boxes on features and execute the detection.

C. Training Details

- Augmentation : Flipud, Fliplr, Rotation, Sheer
- Bounding Box Size: 32*32
- Positive / Negative case ratio: 8:1
- Optimizer : SGD, AdamW

D. Data post-processing

I. Min-fractures Gate: If the number of predicted fractured frame in all data of a single patient is less than n, it is regarded as a false alarm.

II. Consecutive Gate: If the fracture is detected in a single frame (not consecutive), it is regarded as a false alarm.

III. Ensemble Gate: Ensemble YOLOv5 and EfficientDet to predict the skull fractures. (Only fractures detected by both models will be considered.)

Experiment Results

Model	params (M)	Case level accuracy	F1 score
YOLOv5s [1]	7.0	0.59	0.68
YOLOv5x [1]	86.2	0.64	0.74
EfficientDet [2]	52.6	0.58	0.50
Faster R-CNN [3]	41.3	0.59	0.52

Table 1. Results of different model sizes or architectures (w/o post-processing)

Post-processing	YOLOv5 Acc / F1 score	EfficientDet Acc / F1 score
w/o post-processing	0.59 / 0.68	0.58 / 0.50
Post I. Min-fractures Gate	0.86 / 0.70	0.72 / 0.54
Post II. Consecutive Gate	0.59 / 0.72	0.79 / 0.58
Post III. Ensemble Gate	0.75 / 0.58	

Table 2. Comparison results of applying different post-processing approaches

Method	YOLOv5 Acc / F1 score
Baseline	0.58 / 0.68
Stacked	0.62 / 0.70
Stacked + Post I	0.82 / 0.72
Stacked + Post I + Post II	0.81 / 0.69

Table 3. Ablation study for different pre-/post-processing methods

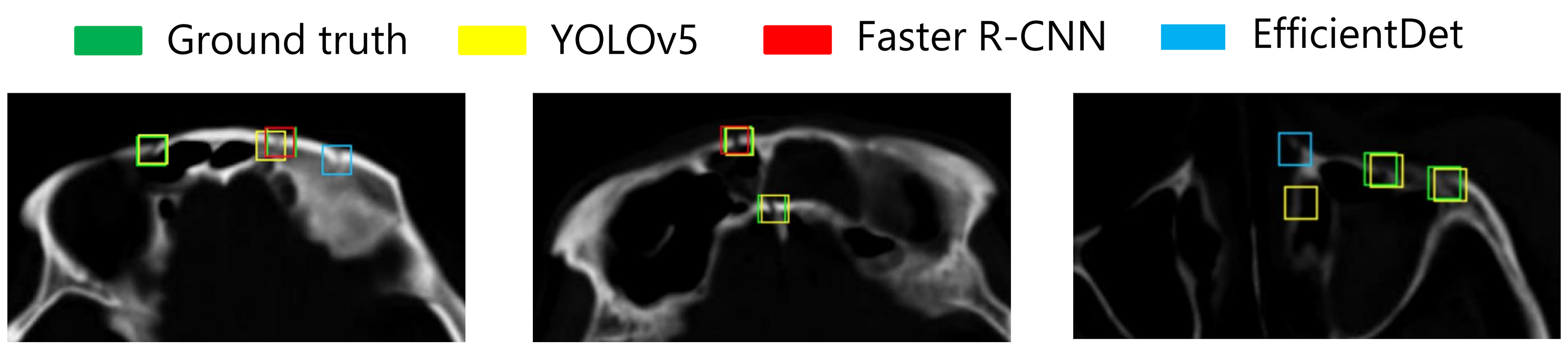


Fig 3. Visualization of results predicted by different models and the ground truth

Conclusion

- We compare the performance of some state-of-the-art models for skull fracture detection. On the validation set, YOLOv5 achieves 0.68 in F1 score, indicating it outperforms EfficientDet and Faster R-CNN in this task.
- It reveals that using approximately 10% background images in the training set is conducive to reducing false positive rate.
- Moreover, with several post-process applied to the predicted result, case-level accuracy and F1-score increase 26.8% and 4.2%, respectively. Hence, we consider a proper post-processing approach can effectively boost the performance in this task.

[1] Glenn Jocher, Alex Stoken, et al. "ultralytics/yolov5: v6.0 - YOLOv5n 'Nano' models, Roboflow integration, TensorFlow export, OpenCV DNN support." *Zenodo*, doi: 10.5281/zenodo.5563715.
[2] Mingxing Tan, Ruoming Pang, et al. "EfficientDet: Scalable and Efficient Object Detection." arXiv:1911.09070 (2020).
[3] Shaoqing Ren, Kaiming He, et al. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks." arXiv:1506.01497 (2016).