DLCV Challenge 1 - Skull Fracture Detection

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Objectives

In this challenge, we are given the computer tomography of different patients with skull fractures. We aim to train a neural network in order to detect whether the patient has skull fractures as well as where those fractures are.

Data Pre-processing

CT images contains sequences of data for each patient. However, the portion of the images with skull fractures is quite low. The imbalanced data will cause the model to predict all the results as negative.To address this problem, we only pick out the skull fracture data for training. Then, we normalized the range of CT image to 0 - 255 as RGB format.

For the data augmentation part, we use "Mosaic" helping our model to learn how to identify objects at a smaller scale than normal. Since skull fractures are small points, this technique helps a lot.

Model and Training

We follow YOLOv5l version 6 architecture and load the weight pre-trained on ImageNet. The following are the hyper-parameter settings for training. Batch size 8, Adam optimizer, and train 500 epochs with 100 early-stop if the validation loss does not improve.

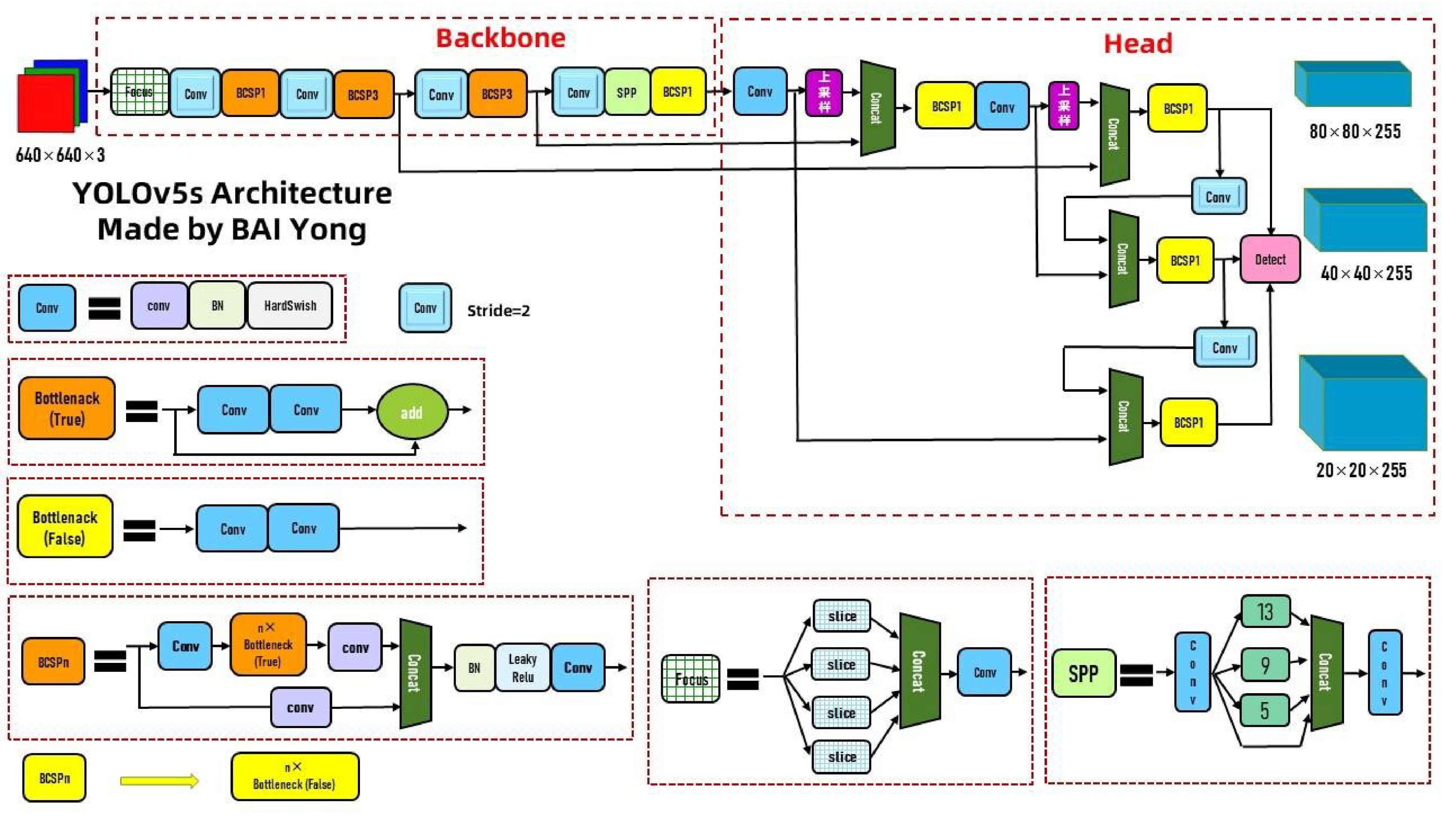

Fig. 1: Model architecture of YOLOv5

We consider three setting for the model input.

1. 3D CT images (concat 20-46 sequence 2D images)
2. 2.5D CT images (concat 3 sequential 2D images)
3. 2D CT images

After experiments, we find that setting (1) is hard to conduct, since we don't have enough computational resource. Besides, we observed that (3) performs better than (2). Finally, we narrowed down our idea, focusing on 2D CT images object detection.

Post Processing

After getting the final predictions from YOLOv5, we can get a set of predicted anchors in the corresponding images.

However, the accuracy of our model in case level isn't accurate enough. Therefore, we observed the ground truth and surprisingly find that **over 90% of skull fractures appear in consecutive CT images.** Therefore, we apply this prior into our post-processing to remove predictions appear in isolation.

Method(Ours)	Before (Case/F1)	After (Case/F1)
Detection	0.5/0.628	**0.86/0.658**
Segmentation	0.51/0.029	0.65/0.034

Fig. 2: Performance comparison before & after post processing

Result

The results of our model are compared with YOLOv3 and Modified Attention UNET, as shown in Fig. 3. As we can see, our model outperforms the other two in F1 Score. It also achieves the case accuracy of 86%, which is close to the state-of-the-art networks.

Method	Case Accuracy	F1 Score
YOLOv3 [2]	85.96%	0.6416
Modified Attention UNET [2]	88.26%	0.4144
OURS	**92.3%**	**0.75**

Fig. 3: Performance comparison of the models

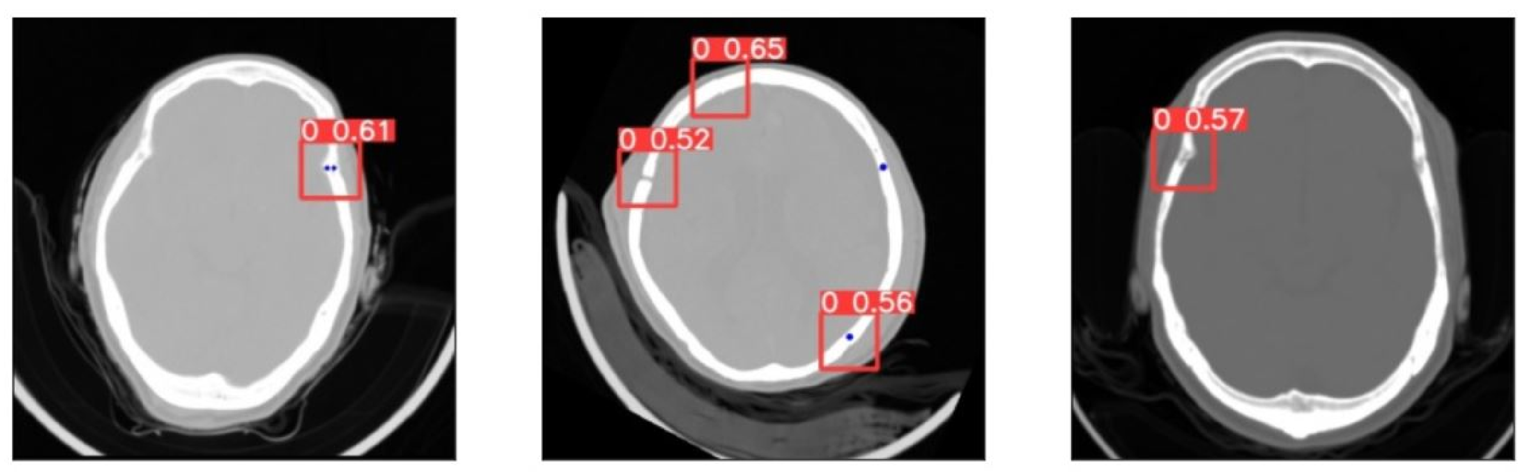

Fig. 4: Prediciton Results(left: prediction | middle: some misprediction | right: missed prediction)

Ablation Study

Since the range of correct prediction following the formula :

$$|\mathbf{x} - \mathbf{x}'| + |\mathbf{y} - \mathbf{y}'| \leq \mathbf{32} \quad (1)$$

We also tried different sizes of kernels to extend the prediction point to an kernel-sized area in order to improve the accuracy rate. Fig.5 is the result of different kernel size.

Kernel size/ Confidence	Case Accuracy	F1 score
19*19	0.846	0.658
15*15	0.861	0.658
3*3	0.861	0.646

Fig. 5: Performance comparison of the models

Conclusion

We propose a 2D object detection model to detect skull fractures. By post-processing our prediction, this method reaches 92.3% case level accuracy and 0.75 F1 score.

References

[1] Gang Liu et al. "Skull Fracture Detection Method Based on Improved Feature Pyramid Network". In: 2021.

[2] Wei Shan et al. "Automated Identification of Skull Fractures With Deep Learning: A Comparison Between Object Detection and Segmentation Approach". In: 2021.

[3] Zhuo Kuang et al. "Skull R-CNN: A CNN-based network for the skull fracture detection". In: 2020.