Auto-WCEBleedGen Challenge

Version V2

Team Name : **ACVLAB**

Team member names and affiliation :

Members	Member Name	Affiliation
Member 1	Chih-Chung Hsu	Associate Professor, Institute of Data Science, National Cheng Kung University, Taiwan
Member 2	Yu-Fan Lin	College Student, Institute of Data Science, National Cheng Kung University, Taiwan
Member 3	Chia-Ming Lee	Graduate, Institute of Data Science, National Cheng Kung University, Taiwan
Member 4	Bo-Cheng Qiu	College Student, Institute of Data Science, National Cheng Kung University, Taiwan

Contact number :

Tel: +886 6-275-7575 #53641

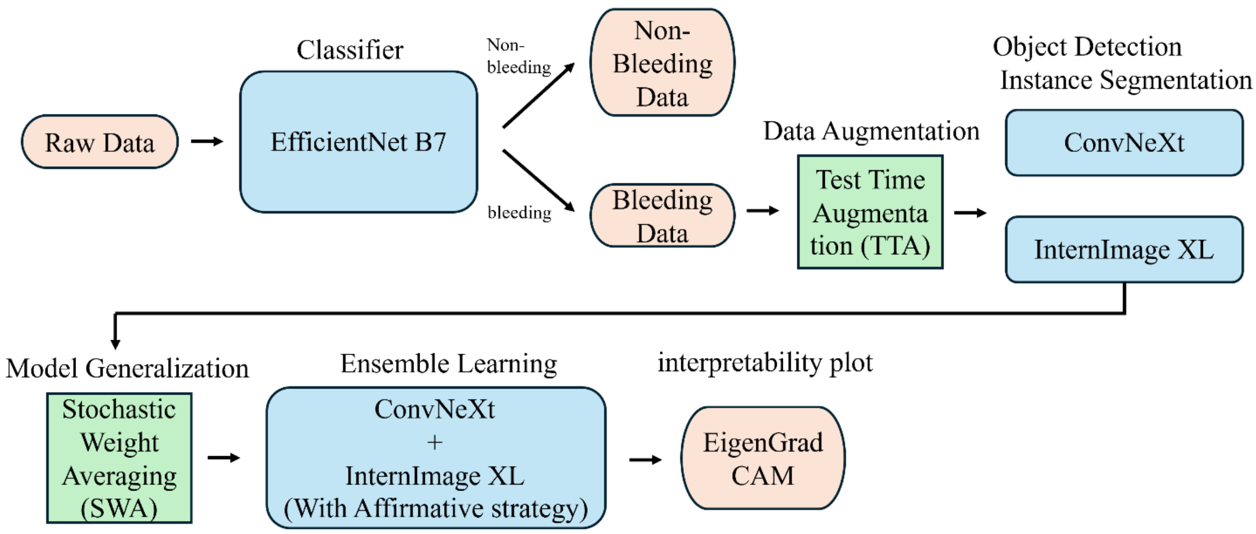
Email address :

cchsu@gs.ncku.edu.tw
zuw408421476@gmail.com
aas12as12as12tw@gmail.com
a36492183@gmail.com

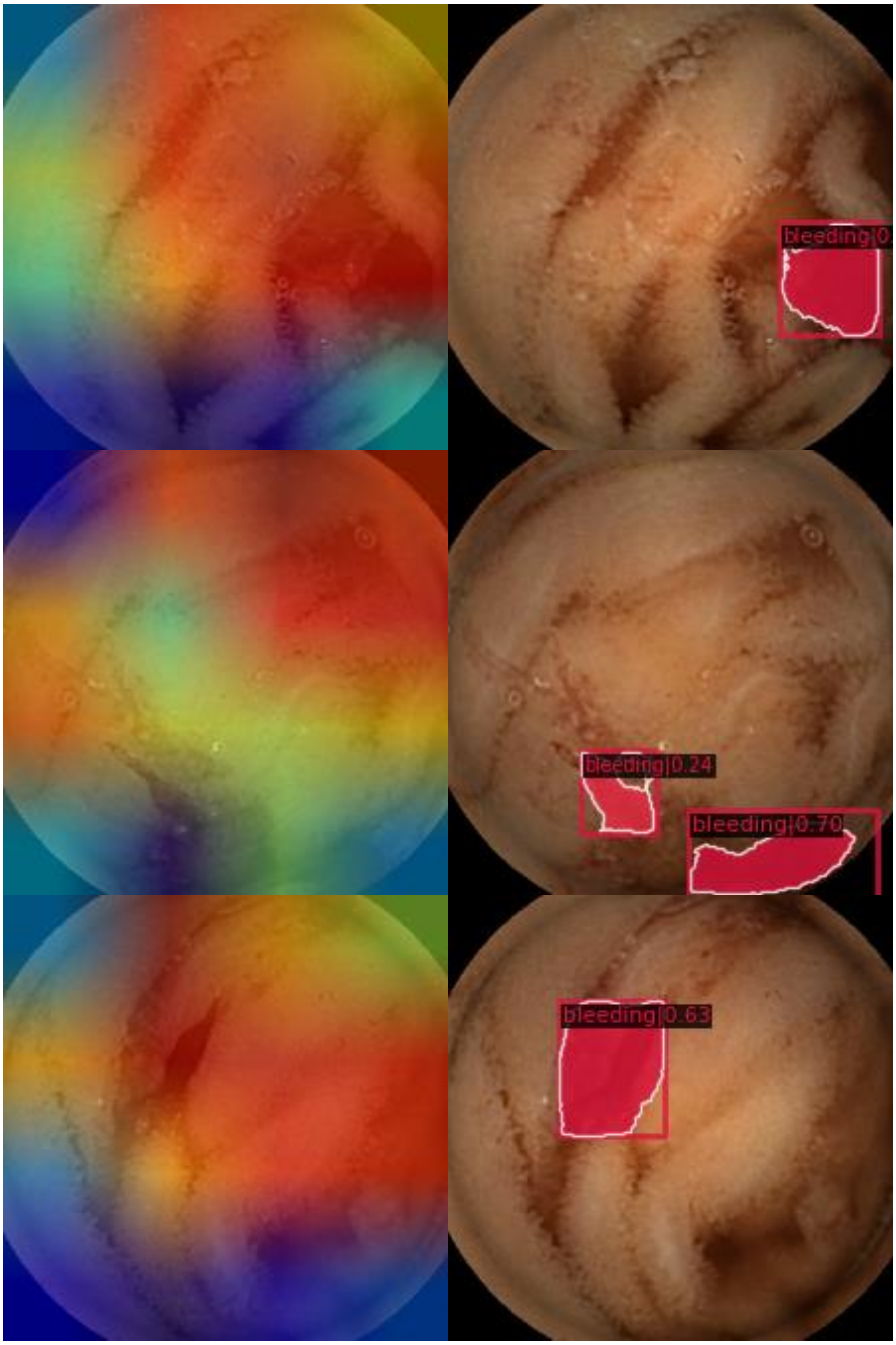
Brief write up about the pipeline :

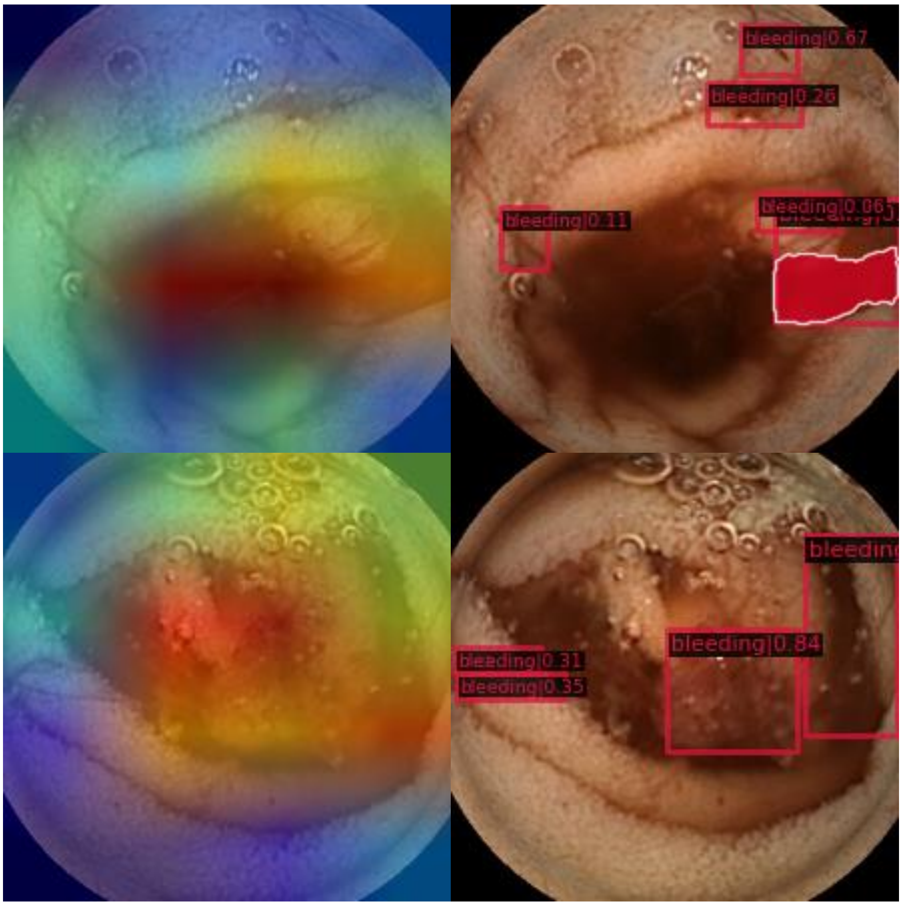
In this competition, we divided the tasks of classification, object detection, and segmentation into two distinct phases. The first phase involved training an EfficientNet B7 model to differentiate images based on the presence or absence of intestinal bleeding, resulting in impressive scores on the evaluation metrics for TestDataset2. The second phase focused on the more detailed detection and instance segmentation of bleeding within the images.
For the object detection and segmentation of images with bleeding, we initially employed Test Time Augmentation (TTA) to enhance our data and trained both ConvNeXt and InternImage XL models. We then applied Stochastic Weight Averaging (SWA) to the last five weights, aiming to improve the models' ability to generalize.
In terms of performance, the ConvNeXt model outperformed the InternImage model in detecting bounding boxes but was less effective in segmentation tasks. To achieve both accurate bounding box detection and high segmentation precision, we integrated the strengths of the ConvNeXt and InternImage models. Additionally, to maximize the detection rate, we implemented an Affirmative strategy, which assumes that the detection of an object by any single model in the ensemble confirms its presence. While this approach increases sensitivity, it may also raise the chance of false positives.
Throughout this process, we managed the predictions by either concatenating or discarding them based on specific criteria, then regenerated bounding boxes for the combined results. In the final visualization stage, we chose the mean channel of the neck component for display. For the interpretive evaluation of both training and test datasets, we utilized EigenGradCAM for insights.

Figure of the development pipeline :



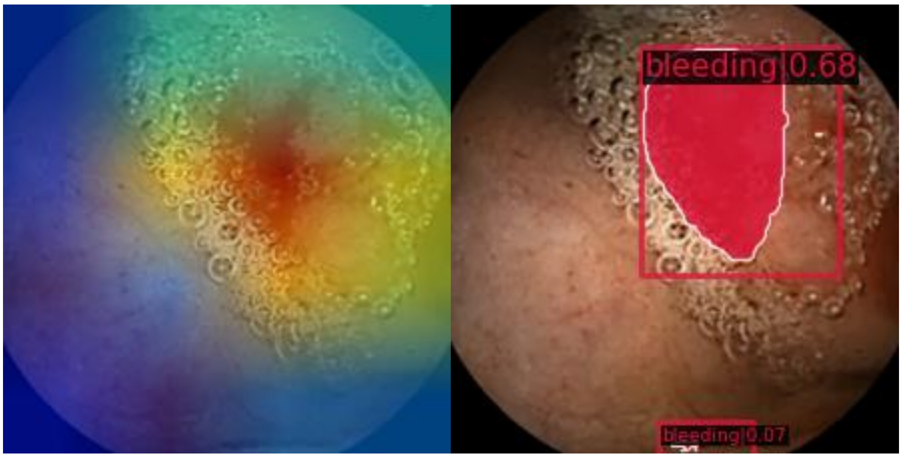
Achieved results on validation dataset including :

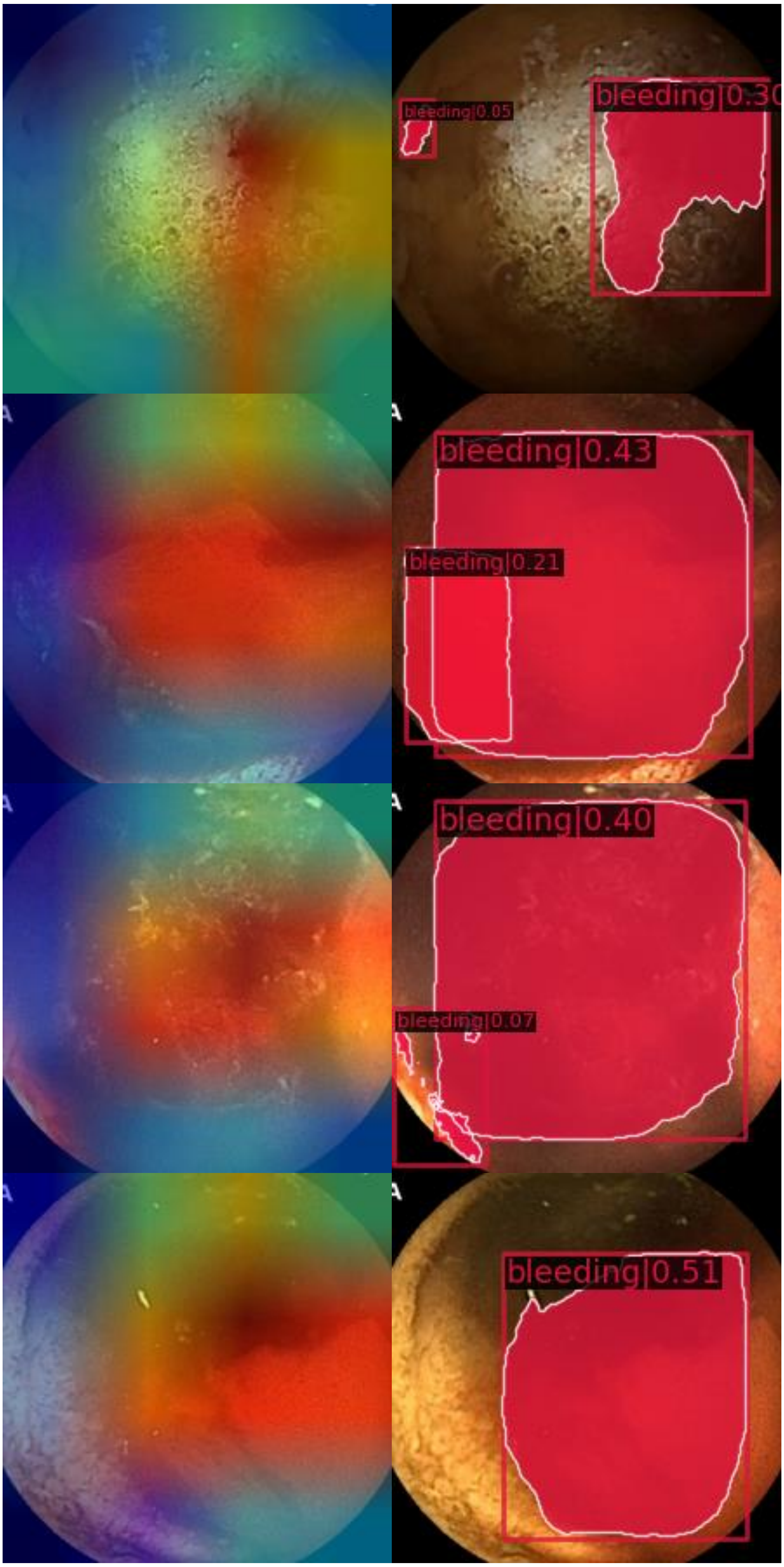




Achieved results on testing dataset including :

Metric	Classification			Detection		Segmentation
S. No	Accuracy	Recall	F1-Score	Average Precision	IoU Score	IoU Score
Test Dataset 1	51.0204	25.5102	33.7837	0.308	0.666	0.4706
Test Dataset 2	74.9514	74.7701	74.6517	0.514	0.7699	0.6318




bleeding|0.05
bleeding|0.3
bleeding|0.43
bleeding|0.21
bleeding|0.40
bleeding|0.07
bleeding|0.51