Auto-WCEBleedGen Challenge

Version V2

Team Name : ColonNet

Team member names and affiliation:

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ABOUT THE MODEL

Network Architecture

The Neural Network consists of three branches for classification, segmentation and bounding box prediction.

Classification & Bounding Box Prediction Branch

- DenseNet121 is used to extract features from the input image. This output is Maxpooled and flattened to pass into the classification branch. For the bounding box branch, the output is Averagepooled and flattened.
- The classification branch consists of 5 fully connected layer connected by ReLU activation function. Dropout layers of 0.3 and 0.2 are implemented after first and second layer. Sigmoid Function is applied on the final layer which has only 1 node.
- The bounding box prediction branch consists of 6 fully connected layers connected by ReLU and ELU activation function. Dropout layer of 0.3 is implemented after

4th layer. Sigmoid Function is applied on the final layer to crunch the values of the coordinates between 0 and 1.

Segmentation Branch

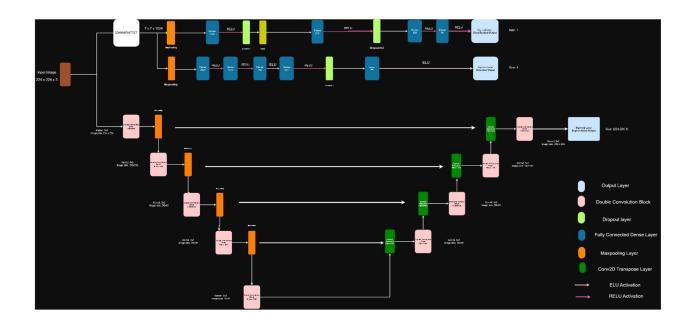
For Semantic Segmentation we have employed the traditional UNet architecture with Batch Normalization and ConvTranspose layers. It comprises of an Encoder path and a Decoder path which generates segmenation masks.

Loss Functions

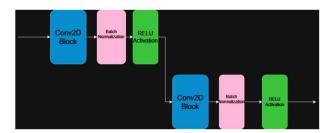
- Classification Branch Binary Cross Entropy Loss
- Bounding Box Prediction Branch Mean Squared Error Loss
- Segmentation Branch Focal Tversky Loss

Training Pipeline

- *AdamW* Optimizer is used for training classification and bounding box branches and *Adam* optimizer is used for training segmentation branch.
- 1. We trained the Bounding Box branch for 10 epochs by feeding only bleeding images to the model. This resulted in *0.1806* validation loss.
- 2. Next we froze the parameters for the bounding box branch and the DenseNet and trained the model again for 10 epochs this time with the entire training dataset including non-bleeding images. At the end the validation loss for classification was *0.001*.
- 3. For segmentation branch, again only bleeding images were passed to the model for 30 epochs. The best validation loss obtained was *0.28*.



(Full Model)



(Double Conv Layer -Used in Unet)

Achieved results on validation dataset

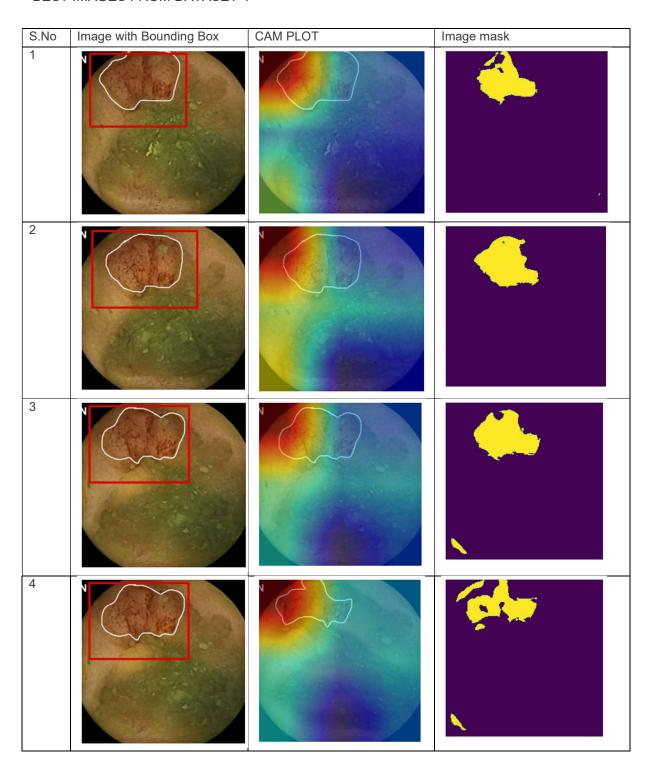
METRICS	VALUES
CLASSIFICATION (ACCURACY)	1.00
BOUNDING BOX (MSE LOSS)	0.1806
SEGMENTATION (IOU)	0.43

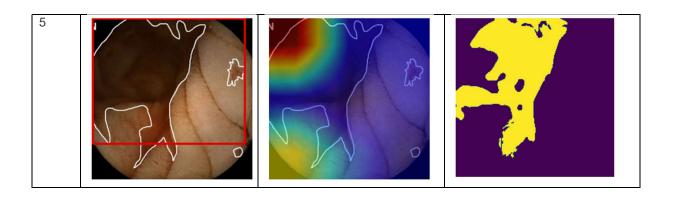
S.No	Image with Bounding Box	CAM PLOT	Image mask
1			
2			
3			
4			
5			

Achieved results on testing dataset including :

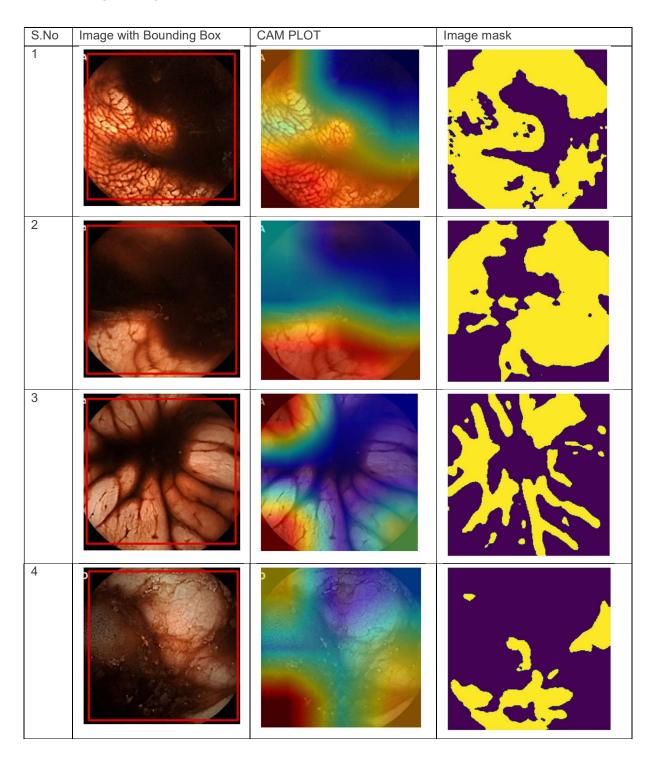
METRICS	DATASET 1	DATASET 2
CLASSIFICATION (ACCURACY)	0.49	0.82
BOUNDING-BOX (MSE LOSS)	0.06	0.15
SEGMENTATION (IOU)	0.20	0.61

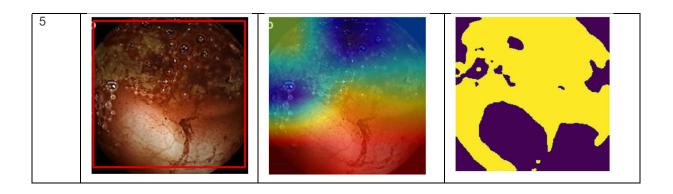
BEST IMAGES FROM DATASET-1





BEST IMAGES FROM DATASET-2





ROC-AUC ANALYSIS

The ROC curves for the DenseNet121 based model and a VGG16 based model are shown below. The models do not differ much by their ROC curves, but the DenseNet121 model holds a slight edge over the VGG16 model. In addition to this, the VGG model took significantly longer amount of time to predict images, approximately 7 minutes for Test set 2, as compared to the DenseNet based model, which required only 90 seconds for the 515 images in test dataset 2. Using the RoC curve we decided to choose a threshold of 0.5 for our Classification model.

