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동서울대학교
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복부 CT(Computed Tomography) 이미지 객체 분할 작업 성능 개선에 관한 연구

한국통신학회 하계종합학술발표회2024

Computer Software

장기태

Contents

1. What is SAM

Meta

1. GPT trained on Next token prediction performs well on various tasks.

2. Develop a new task, model, and dataset in Computer Vision with the aim of creating such a versatile model.

3. Segmentation is naturally well-executed, and it shows decent performance on other tasks as well.

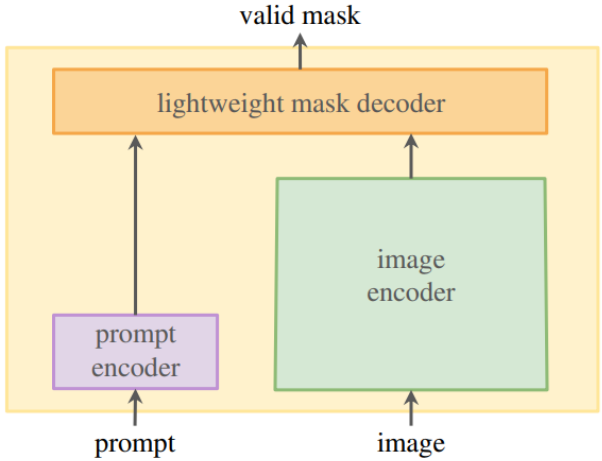
https://segment-anything.com/demo

1. What is SAM

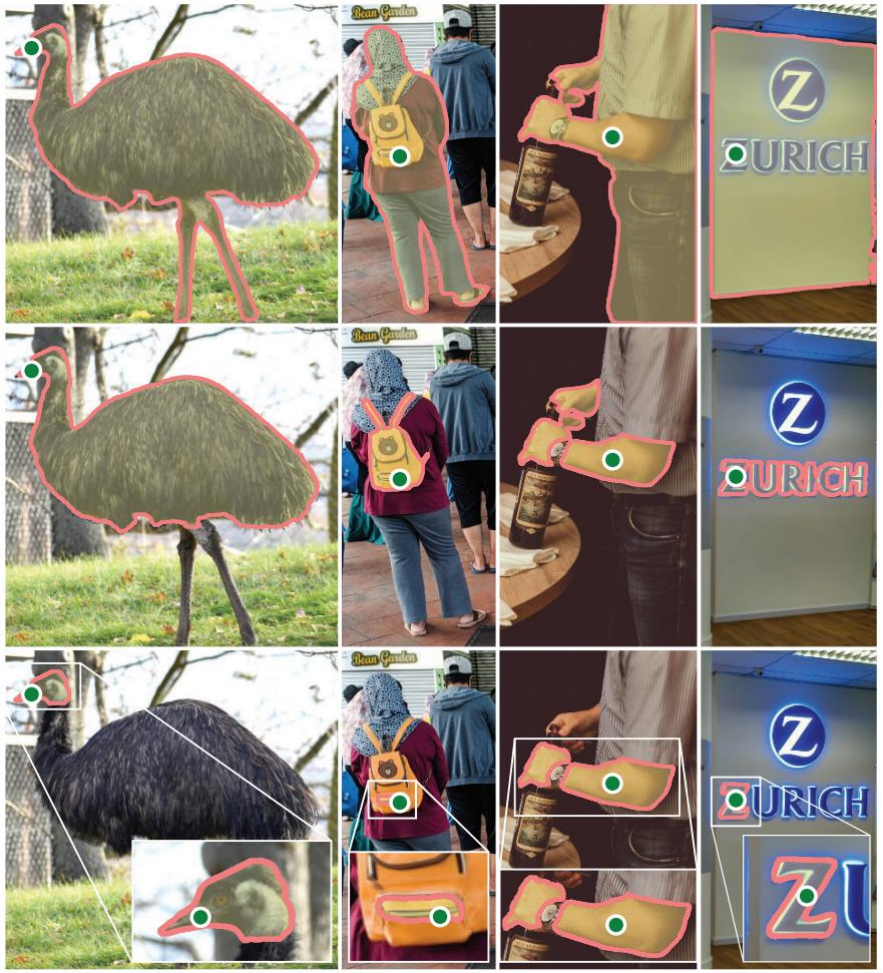
Segment Anything Model

Refers to a deep learning model that identifies and segments objects in visual data such as images or videos

SAM is primarily used for image segmentation tasks, accurately delineating the boundaries of objects within an image to segment them.



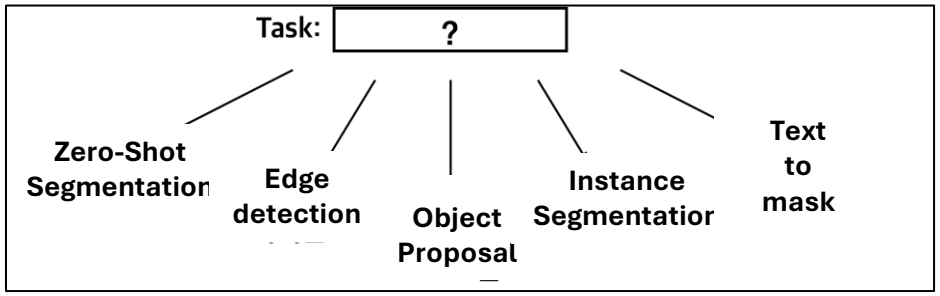
(b) **Model**: Segment Anything Model (**SAM**)

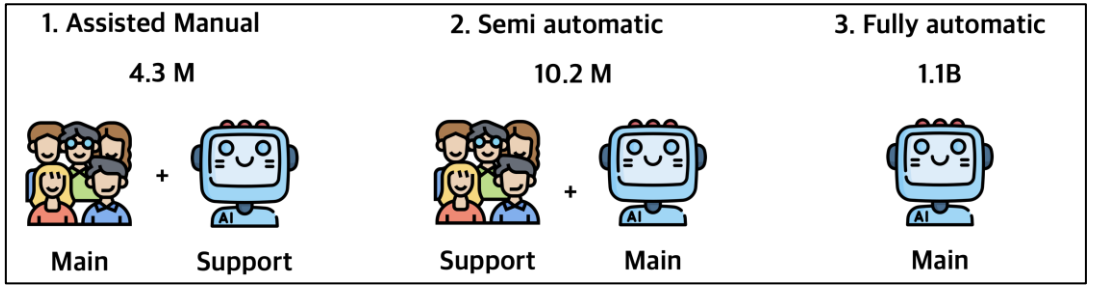


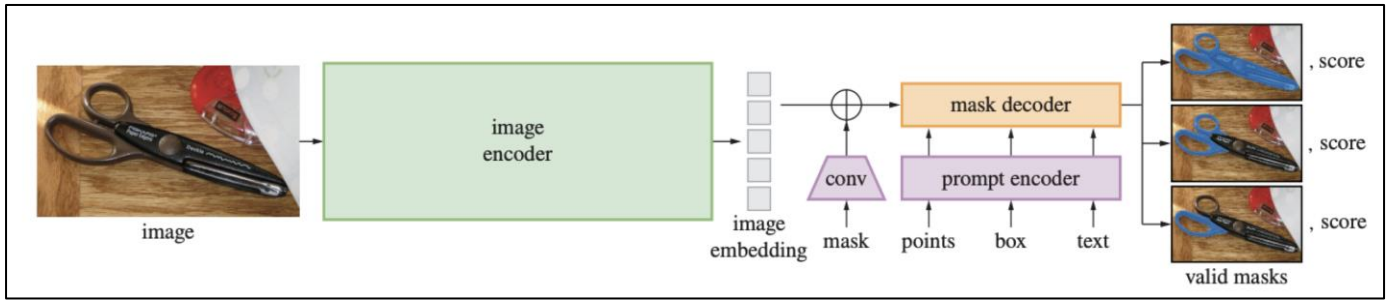
2. Primary Contribution

SAM

- Task
- Data
- Model

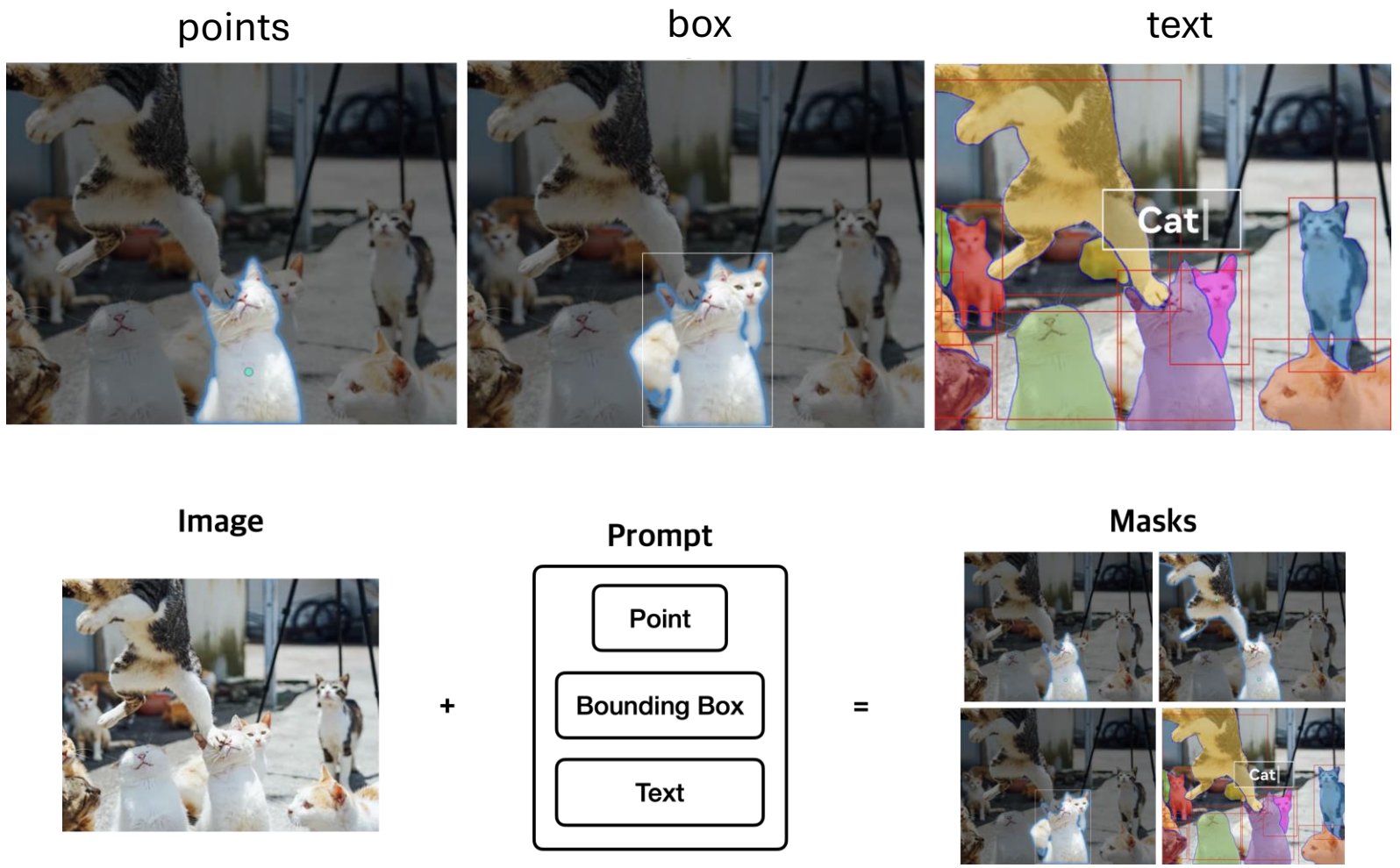






2. Primary Contribution(Task)

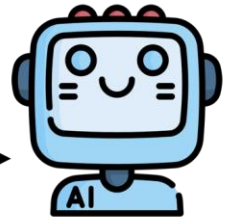
Promptable Segmentation



2. Primary Contribution(Data)

1. Assisted Manual

Dataset
LVIS v1
MS COCO
ADE20
Open Images

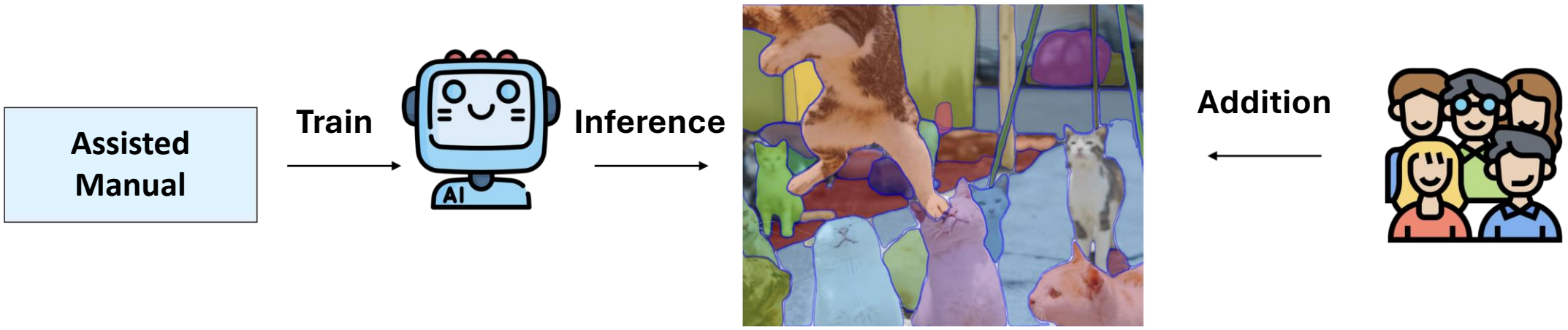
Train → 

Inference →

Modification
Addition ←

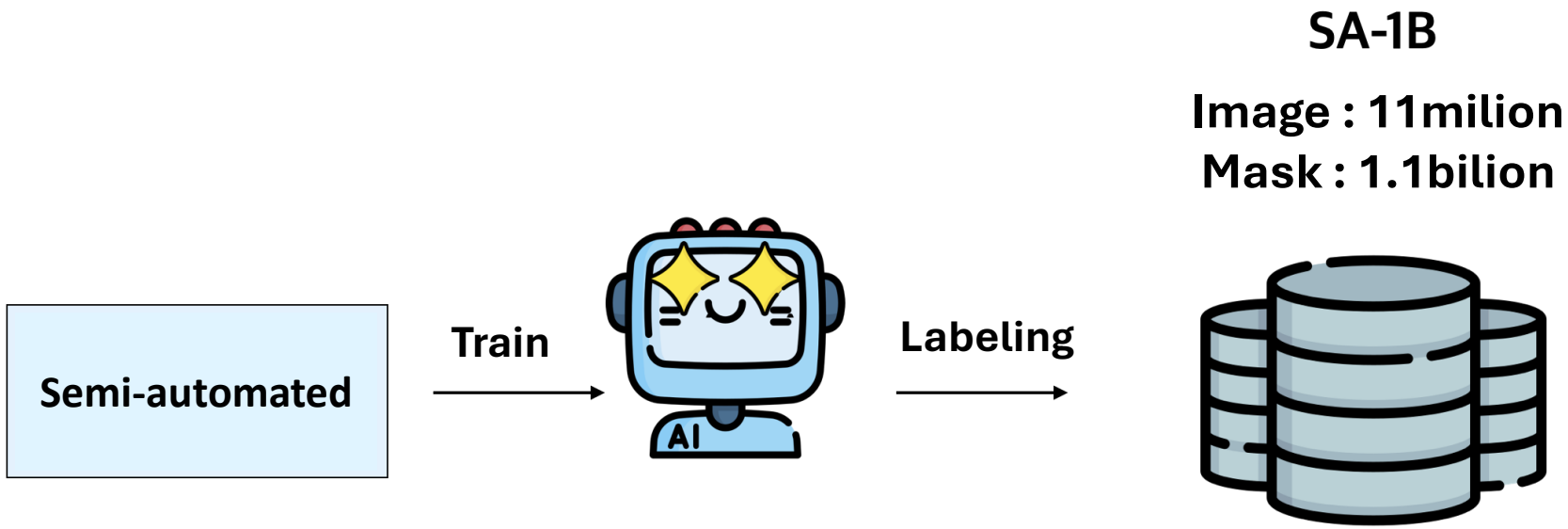
2. Primary Contribution(Data)

2. Semi-automated



2. Primary Contribution(Data)

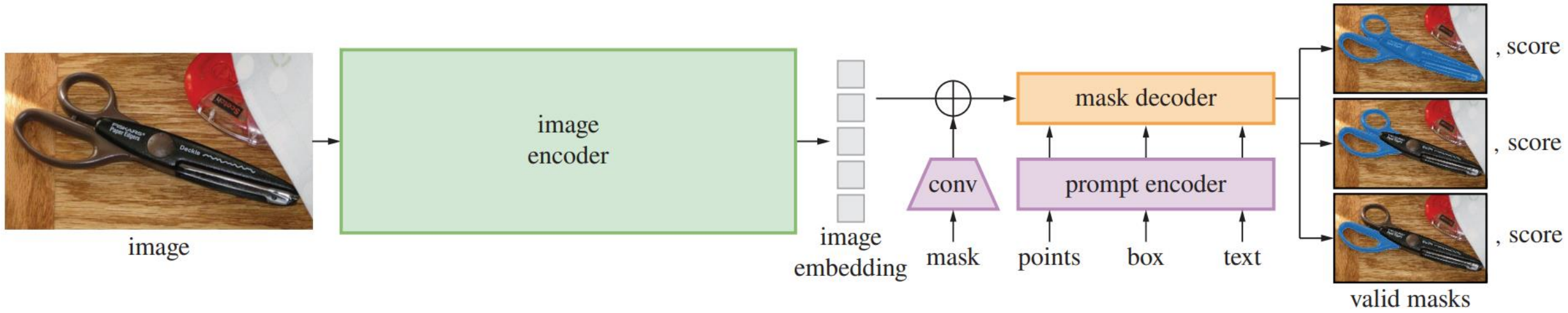
3. Fully-automated



2. Primary Contribution(Model)

Model Architecture

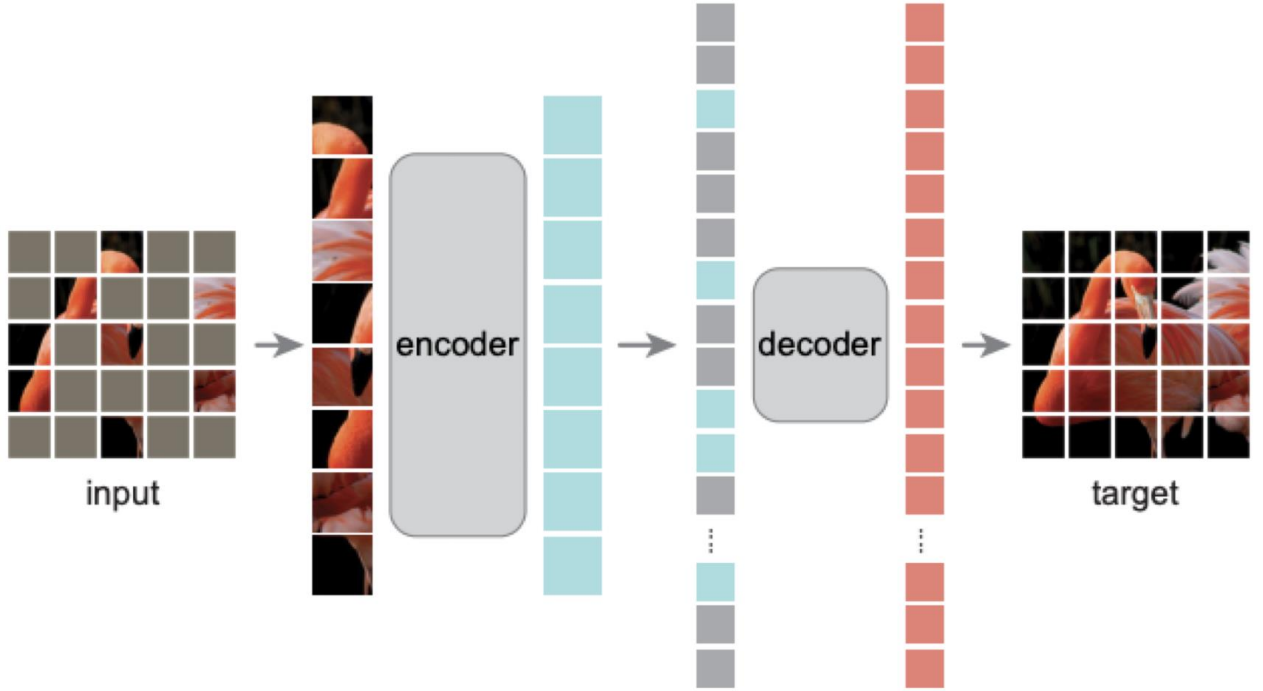
1. **Image Encoder**
   Image encoder extracts features from the given image.
   It is typically based on Convolutional Neural Network
2. **Prompt Encoder**
   Prompt encoder converts textual prompts into vector representations.
3. **Mask Decoder**
   Mask decoder rapidly segments objects based on images and textual prompts.
   This decoder generates masks used for object segmentation by combining image and text information.



2. Primary Contribution(Model)

1. Image Encoder

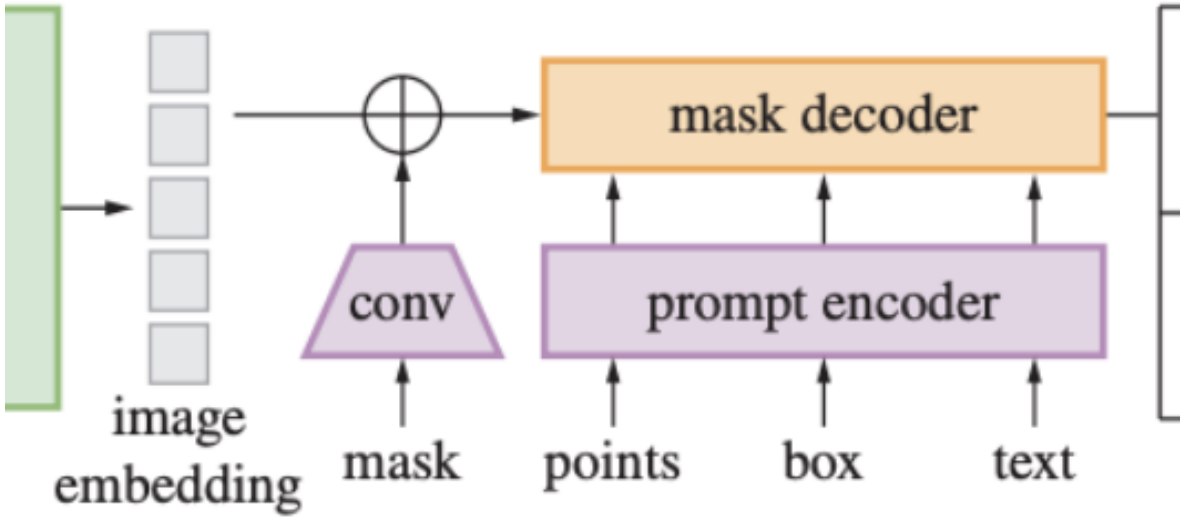
- The Image Encoder utilizes a Vision transformer trained with Masked Auto-Encoder (MAE) approach.
- MAE divides the image into a grid of fixed size, randomly masks parts of it, and trains the model to reconstruct.
- Only the encoder is used in the model, excluding the decoder.



2. Primary Contribution(Model)

2. Prompt Encoder

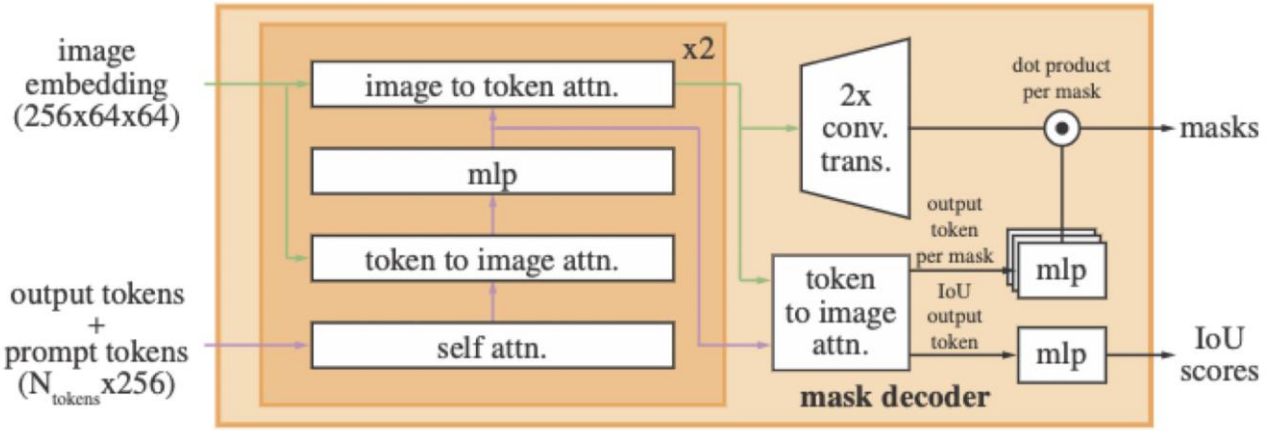
- **Sparse prompts** (points, boxes, text): Embedded into a 256-dimensional vector.
  - Points : The position of the dot is encoded using positional encoding + foreground/background embedding.
  - Boxex : positional encoding + top-left corner / bottom-right corner
  - Text : text encoder from CLIP
- **Dense prompts** (masks): convolutions and summed element-wise with the image embedding



2. Primary Contribution(Model)

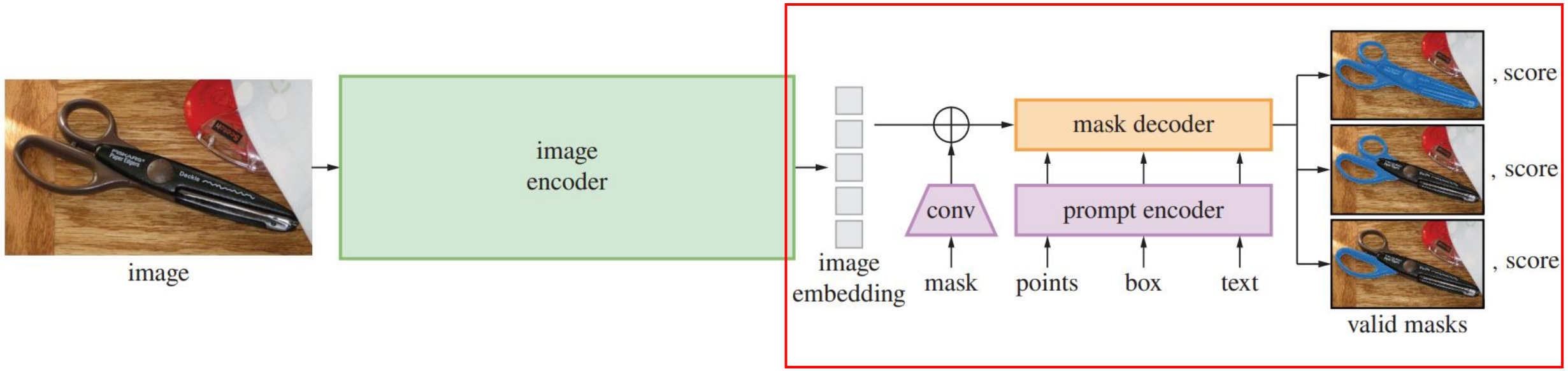
3. Mask Decoder

1) Self-attention on the tokens
2) Cross-attention from tokens to the image embedding
   (query : token / key, value : image)
3) Point-wise MLP updates each token
   A linear layer is applied to channels per pixel.
4) Cross-attention from the image embedding to token
   (query : image / key, value : token)
5) Token to image cross attention -> Output token
6) The image embedding, passed through attention, is upsampled using convtranspose to increase the spatial size by 4 size.

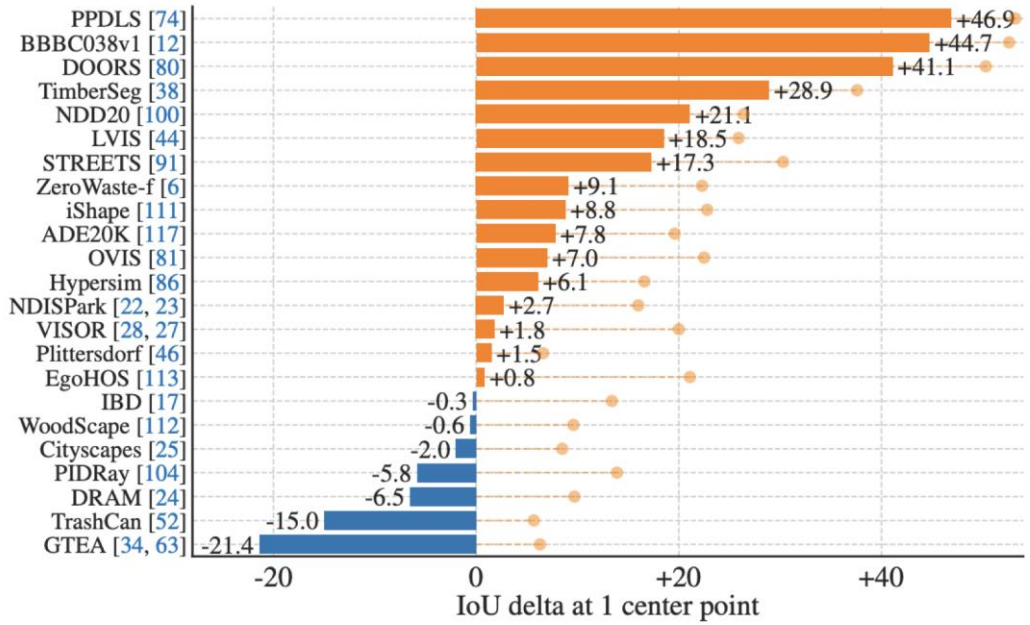


2. Primary Contribution(Model)

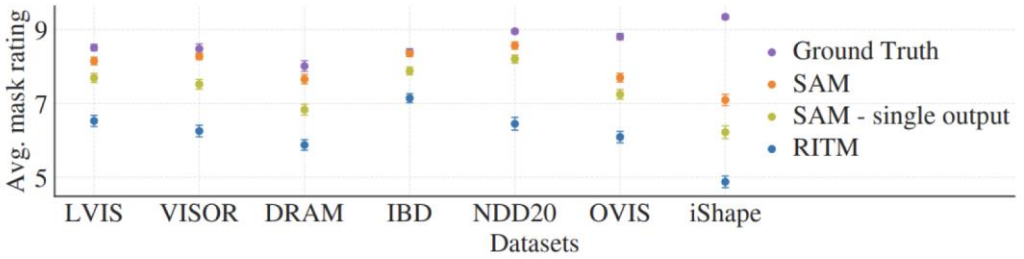
3. Mask Decoder



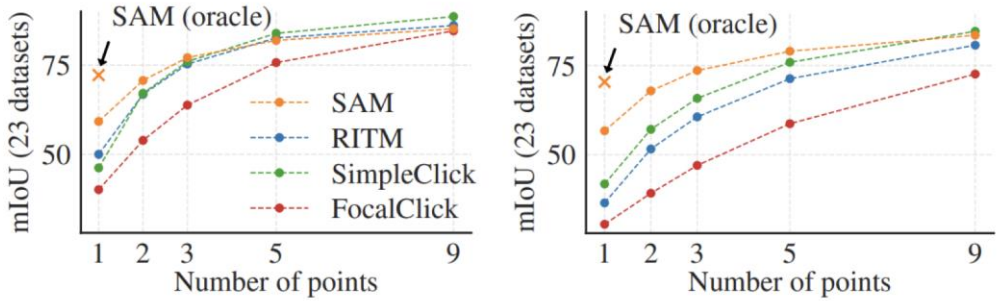
3. Sam experiment



(a) SAM *vs.* RITM [92] on 23 datasets



(b) Mask quality ratings by human annotators



(c) Center points (default)

(d) Random points

- The segmentation result for the one point prompt.
- Compared to RITM, SAM demonstrates superior performance on 16 out of 23 datasets.

- Comparison based on mask quality scores assigned by human annotators.

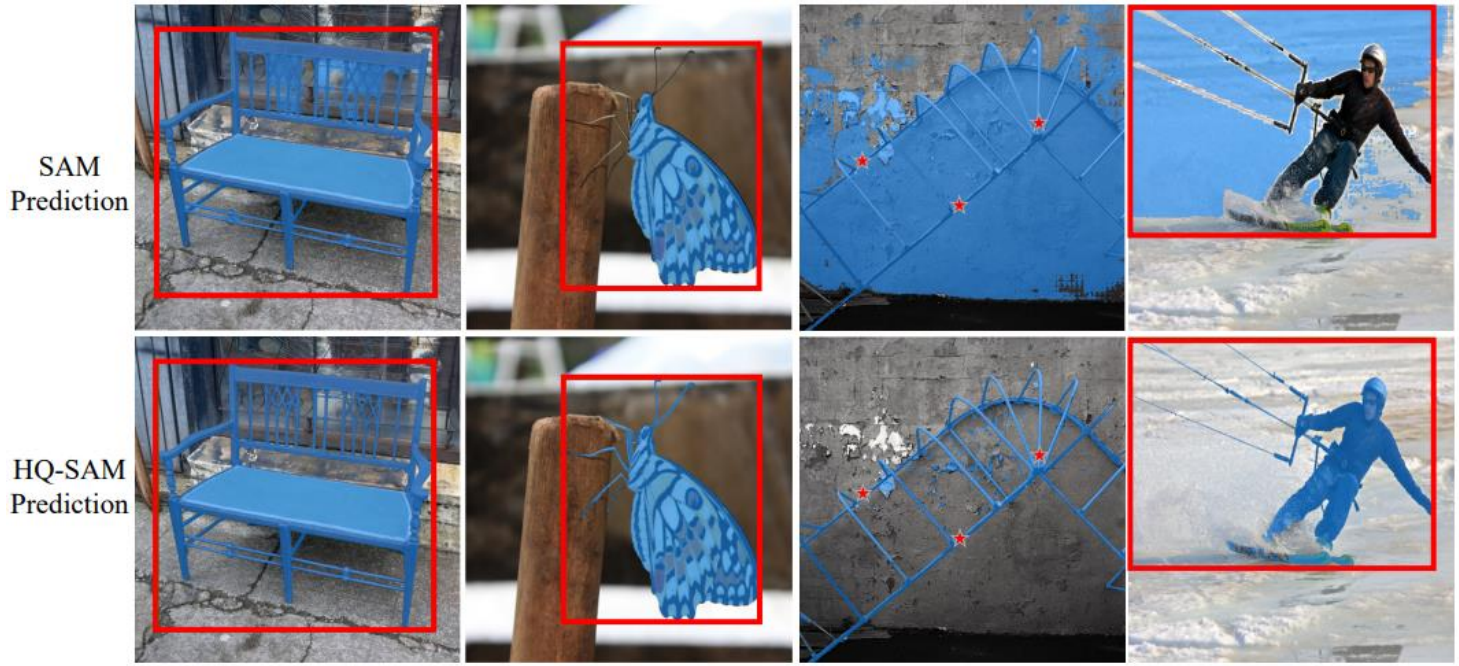
4. HQ-SAM

Segment Anything in High Quality

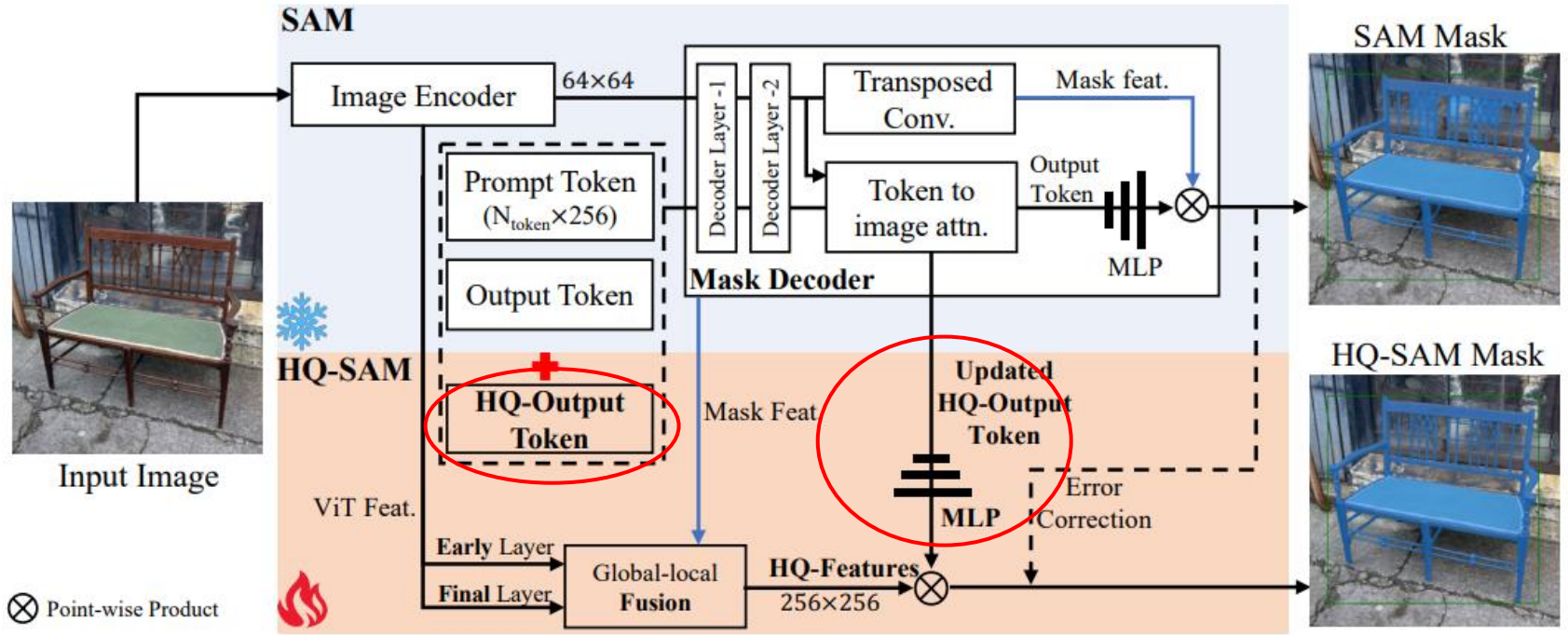
1.It often ignores segmentation of thin object structures.

2.It introduces large errors for broken masks and tricky cases.

Propose HQ-SAM, which can predict a highly accurate segmentation mask even in very difficult cases without compromising the powerful zero-shot capability and flexibility of SAM.



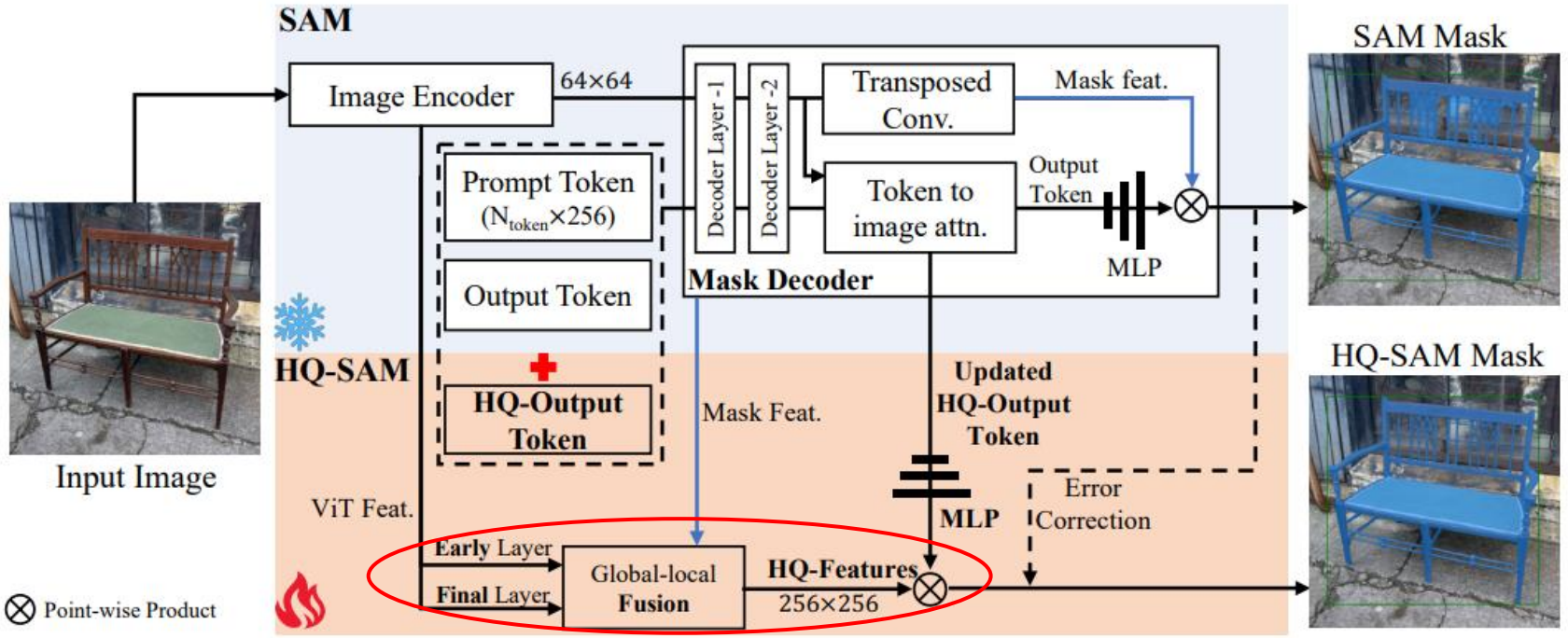
4. HQ-SAM



- HQ-Output Token

-SAM : prompt token(N_{promts} X 256) + output token(4 X 256) -> decoder
-HQ-SAM : : prompt token(N_{promts} X 256) + output token(4 X 256) + HQ-output token -> decoder

4. HQ-SAM



- Global-local Fusion for HQ-Features

To effectively learn both the local features such as the edges and boundary details of the image and the global context, the information from the **early layers** and **final layers** of SAM's image encoder is combined for use.

4. HQ-SAM

Model	AP_B^{strict}	AP_{B75}^{strict}	AP_{B50}^{strict}	AP_B	AP_{B75}	AP_{B50}	AP
SAM	8.6	3.7	25.6	17.3	14.4	37.7	29.7
HQ-SAM	**9.9**	**5.0**	**28.2**	**18.5**	**16.3**	**38.6**	**30.1**

1) A table comparing zero-shot open-world instance segmentation results in UVO.

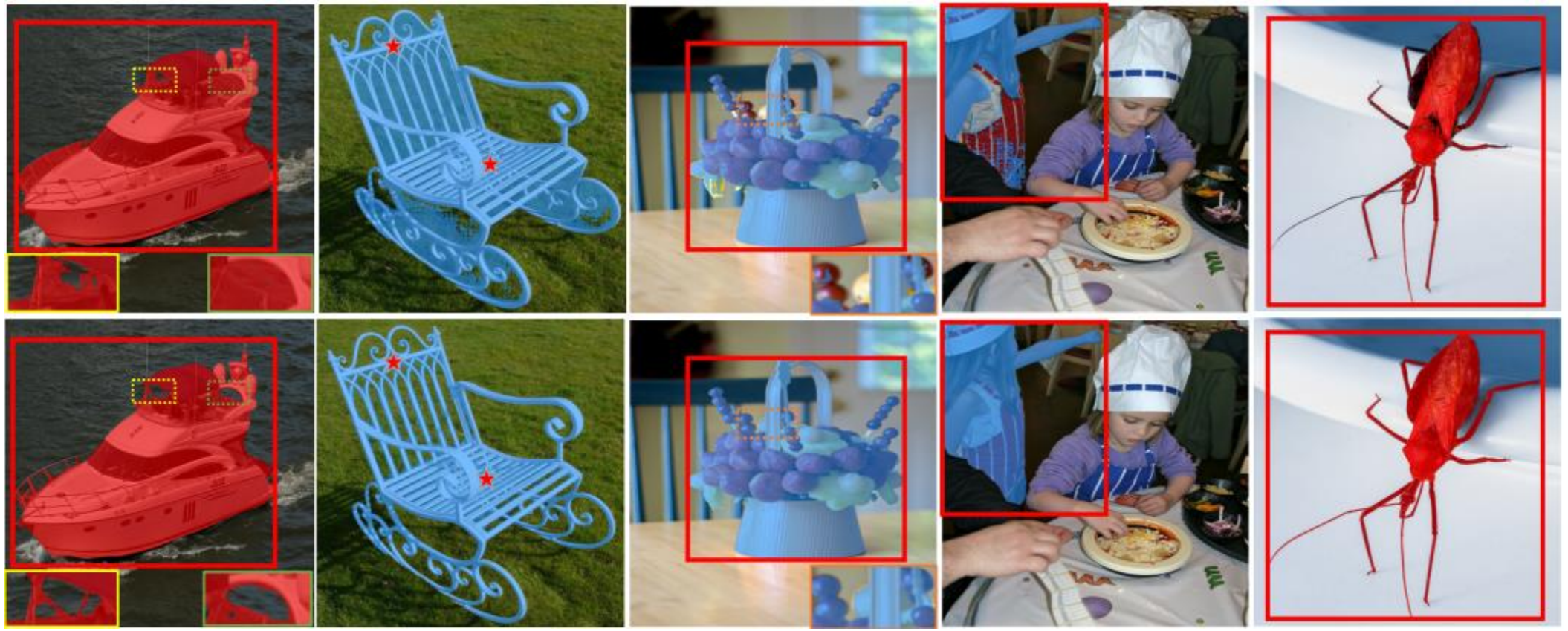
Model	GT Box Prompt		Mask Prompt	
	mIoU	mBIoU	mIoU	mBIoU
SAM	81.1	70.4	66.6	41.8
HQ-SAM	**86.0**	**75.3**	**86.9**	**75.1**

2) A table comparing zero-shot segmentation results on high-quality BIG benchmarks

Model	COCO		LVIS				
	AP_B	AP	AP_B^{strict}	AP_{B75}^{strict}	AP_B	AP_{B75}	AP
SAM	33.3	48.5	32.1	32.8	38.5	40.9	43.6
HQ-SAM	**34.4**	**49.5**	**32.5**	**33.5**	**38.8**	**41.2**	**43.9**

3) A table comparing zero-shot instance segmentation results on COCO and LVISv1 datasets.

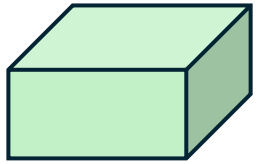
4. HQ-SAM



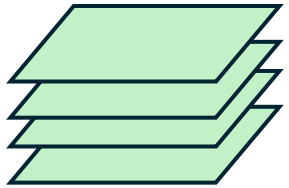
5. Our proposed Method

- **Slice the 3D abdominal images into 2D images.**
- **Input the sliced images.**
- **Perform fine-tuning (freeze the weights of the Image Encoder and Prompt Encoder, and train only the Mask Decoder).**
- **Compare the output mask results with the ground truth.**

FLARE22 Challenge Dataset

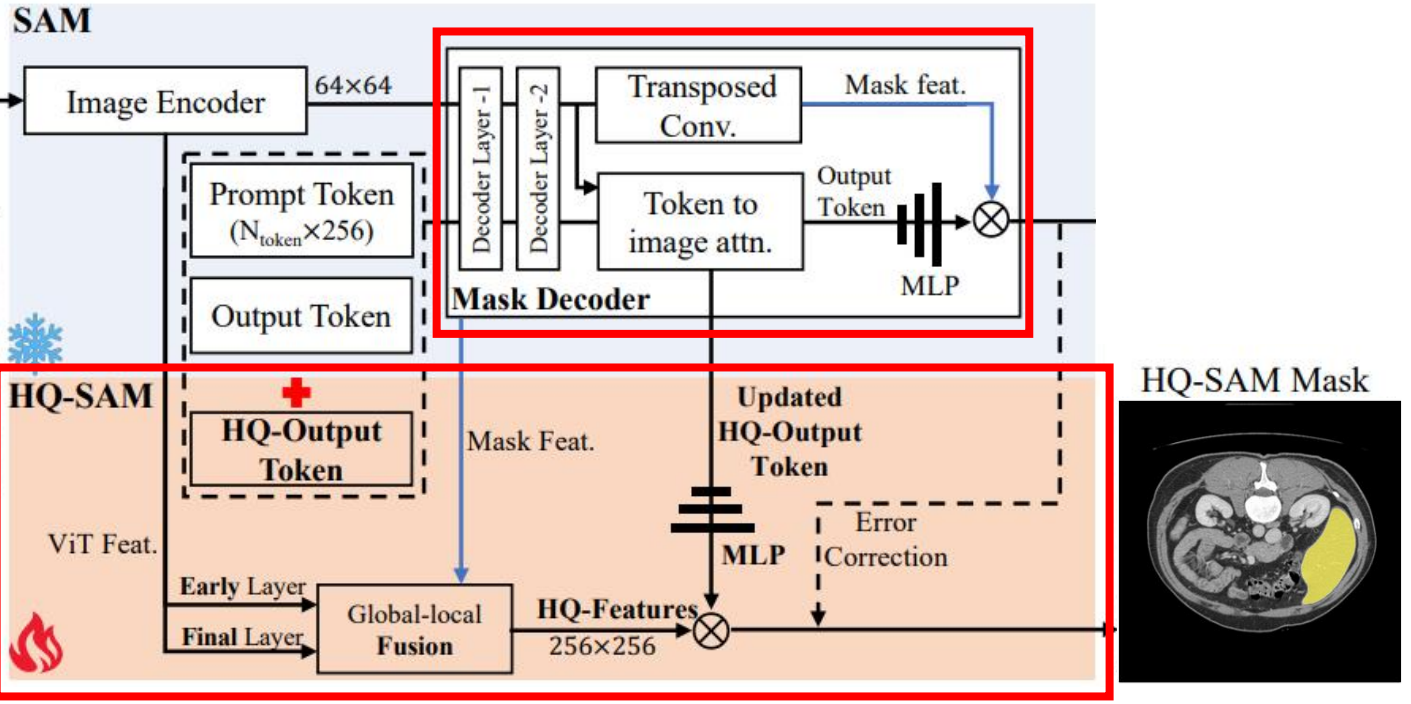


Abdominal CT Image (3D)



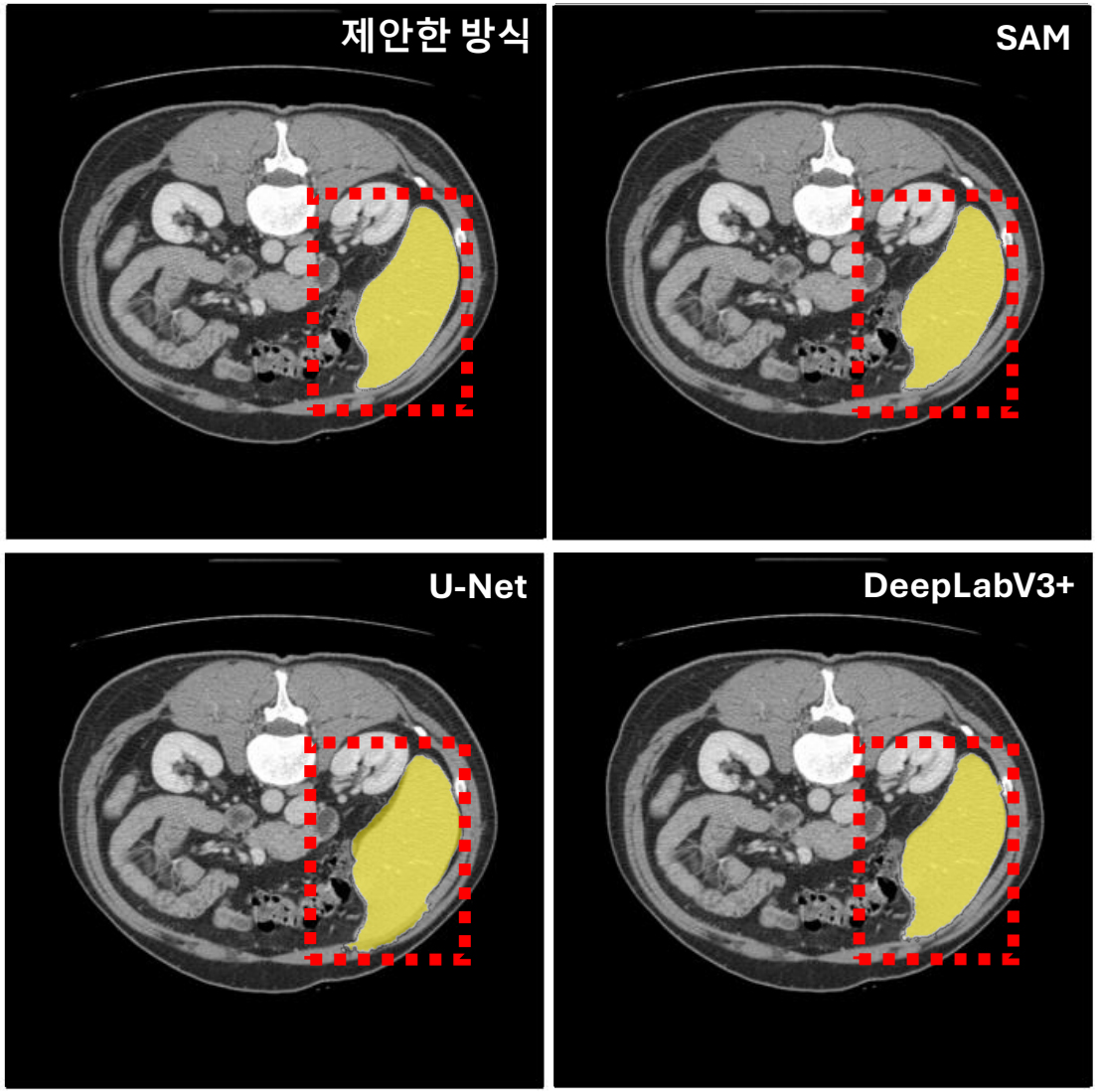
2D Image (Slice)

Input Image



6. Experiment

- Compare the output images with the ground truth images (Dice Score).
- Fine-tune SAM, Unet, and DeepLabV3+ in the same manner.
- Evaluate the four methods using the validation dataset. (FLARE22 Challenge Dataset 20%)



Result

평가방식 / 적용모델	Dice Score
SAM	0.9169
U-NET	0.8420
DeepLabV3+	0.8994
제안한 방식(HQ-SAM)	0.9359