Table 1. Performance Comparison Across CLIP Architectures and Post-processing Methods. Comparative evaluation of our approach against state-of-the-art methods (Trident and CLIPer) across different CLIP architectures (CLIP-ViT-B/16, CLIP-ViT-L/14, OpenCLIP-ViT-H/14) with and without post-processing. Best results are shown in bold, second-best results are underlined. Note: CorrCLIP is not included in the comparison as its implementation is not publicly available.

Method	Post-processing	With background			Without background					Avg.
		VOC21	Context60	COCO-Obj	VOC20	City	Context59	ADE	Stuff	
Without Post-processing										
CLIP-ViT-B/16										
CLIPer(Sun et al., 2024a)	NO	60.1	34.8	36.0	84.0	-	38.5	19.8	25.3	-
Trident(Shi et al., 2024)	NO	64.5	37.2	**39.5**	83.7	40.4	40.9	20.9	**27.6**	44.5
Ours	NO	**66.1**	**37.7**	39.4	**85.4**	**42.8**	**41.2**	**21.0**	27.3	**44.8**
CLIP-ViT-L/14										
CLIPer(Sun et al., 2024a)	NO	61.2	34.3	39.6	**88.2**	-	39.8	21.8	25.8	-
Trident(Shi et al., 2024)	NO	61.4	36.4	40.2	84.8	40.4	39.8	**23.2**	26.4	42.5
Ours	NO	**67.0**	**37.3**	**40.2**	85.5	**42.7**	**41.0**	22.9	**27.1**	**45.5**
OpenCLIP-ViT-H/14										
CLIPer(Sun et al., 2024a)	NO	58.0	34.1	39.2	85.8	-	36.9	22.1	25.2	-
Trident(Shi et al., 2024)	NO	68.6	38.2	**40.8**	**87.7**	**43.6**	42.6	**25.4**	28.0	46.6
Ours	NO	**69.1**	**39.0**	40.0	86.9	43.0	**42.8**	24.5	**28.1**	**46.7**
With Post-processing										
CLIP-ViT-B/16										
CLIPer(Sun et al., 2024a)	YES	65.9	37.6	39.0	85.2	-	41.7	21.4	27.5	-
Trident(Shi et al., 2024)	YES	67.1	38.6	**41.1**	84.5	42.9	42.2	21.9	28.3	45.8
Ours	YES	**70.4**	**39.8**	40.8	**86.2**	**46.4**	**43.6**	**22.2**	**28.7**	**47.3**
CLIP-ViT-L/14										
CLIPer(Sun et al., 2024a)	YES	69.8	38.0	**43.3**	**90.0**	-	43.6	**24.4**	28.7	-
Trident(Shi et al., 2024)	YES	62.6	37.3	40.5	85.5	43.0	40.9	24.0	27.1	44.3
Ours	YES	**71.3**	**39.6**	40.7	86.5	**46.4**	**43.7**	23.8	**28.8**	**47.6**
OpenCLIP-ViT-H/14										
CLIPer(Sun et al., 2024a)	YES	**88.9**	39.3	**42.8**	**88.8**	-	43.2	24.4	28.3	-
Trident(Shi et al., 2024)	YES	70.8	40.1	42.2	88.7	**47.6**	44.3	**26.7**	28.6	**48.6**
Ours	YES	71.7	**40.5**	41.4	87.6	47.0	**44.8**	25.6	**28.8**	48.4

Table 2. Ablation Study on Different VFM Feature Extractors. We compare four DINO variants: ViT-Base with patch sizes of 8 (B8) and 16 (B16), and ViT-Small with patch sizes of 8 (S8) and 16 (S16); two DINOV2 variants: ViT-B/14 and ViT-S/14; and the ViT-B/16 architecture from SAM. Best results are shown in bold.

Model	Dataset							
	VOC21	Context-60	COCO	VOC20	Cityscapes	Context-59	ADE20K	COCO-Stuff
DINO								
ViT-B/8	**70.41**	**39.82**	**40.80**	86.18	**46.41**	**43.56**	**22.24**	**28.72**
ViT-B/16	69.26	39.67	40.46	85.99	45.56	42.47	22.11	27.88
ViT-S/8	69.96	39.49	40.63	86.02	45.94	42.79	22.17	28.24
ViT-S/16	68.91	39.12	40.27	85.88	45.23	42.01	21.96	27.42
DINOV2								
ViT-S/14	68.26	39.13	40.66	**86.61**	44.33	43.09	21.78	28.41
ViT-B/14	68.17	39.03	40.57	86.50	44.59	43.07	21.87	28.48
SAM								
ViT-B/16	68.36	38.0	38.84	84.33	43.64	40.68	21.16	27.37

Table 3. Performance comparison of our approach with other methods on eight semantic segmentation benchmarks. We report results on: **With background category**: VOC21, Context60, COCO-Obj; **Without background category**: VOC20, City, Context59, ADE, Stuff. The best and second-best results are marked in **bold** and underline, respectively. The shaded region ours(SD) represents results obtained by processing our final feature maps using the SD model following CLIPer's(Sun et al., 2024a) approach.

Method	Post-processing	With background			Without background					Avg.
		VOC21	Context60	COCO-Obj	VOC20	City	Context59	ADE	Stuff	
GroupViT(Xu et al., 2022)	No	50.4	18.7	27.5	79.7	11.1	23.4	9.2	15.3	27.7
TCL(Cha et al., 2023)	No	51.2	24.3	30.4	77.5	23.1	30.3	14.9	19.6	33.1
C-Dsier(Wysoczańska et al., 2023)	No	62.2	32.4	35.0	80.2	31.7	35.9	20.0	24.6	40.3
CoDe(Wu et al., 2024)	No	57.5	30.5	32.3	-	28.9	-	17.7	23.9	-
CLIP(Radford et al., 2021)	No	20.8	9.3	8.9	49.1	6.7	11.2	3.2	5.7	14.4
ReCo(Shin et al., 2022)	No	25.1	19.9	15.7	57.7	21.6	22.3	11.2	14.8	23.7
MaskCLIP(Ding et al., 2023)	No	38.8	23.6	20.6	74.9	12.6	26.4	9.8	16.4	27.9
CLIPSurgery(Li et al., 2023)	No	55.2	30.3	29.7	77.5	33.1	33.4	16.1	22.2	37.2
GEM(Bousselham et al., 2024)	No	46.2	32.6	33.9	79.9	21.2	35.9	15.7	23.7	36.1
SCLIP(Wang et al., 2025)	No	59.1	30.4	30.5	80.4	32.2	34.2	16.1	22.4	38.2
ClearCLIP(Lan et al., 2025b)	No	57.0	32.2	32.5	82.3	32.8	35.8	17.3	24.0	39.2
CAR(Sun et al., 2024b)	No	48.6	13.6	15.4	73.7	-	18.4	5.4	-	-
OVDiff(Karazija et al., 2023)	No	66.3	29.7	34.6	80.9	23.4	32.9	14.1	20.3	37.8
LAVG(Kang & Cho, 2025)	No	62.1	31.6	34.2	82.5	26.2	34.7	15.8	23.2	38.8
ProxyCLIP(Lan et al., 2025a)	No	61.3	35.3	37.5	80.3	38.1	39.1	20.2	26.5	42.3
CLIPer(Sun et al., 2024a)	No	60.1	34.8	36.0	84	-	38.5	19.8	25.3	-
SCCLIP(Bai et al., 2024)	No	64.6	36.8	37.7	84.3	41.0	40.1	20.1	26.6	43.9
Trident(Shi et al., 2024)	No	64.5	37.2	**39.5**	83.7	40.4	40.9	20.9	27.6	44.5
Ours	No	**66.1**	**37.7**	39.4	**85.4**	**42.8**	**41.2**	**21.0**	**27.3**	**44.8**
Post-processing										
NACLIP(Hajimiri et al., 2024)	Yes	64.1	35.0	36.2	83.0	38.3	38.4	19.1	25.7	42.5
CLIPer(Sun et al., 2024a)	Yes	65.9	37.6	39.0	85.2	-	41.7	21.2	27.5	-
Trident(Shi et al., 2024)	Yes	67.1	38.6	**41.1**	84.5	42.9	42.2	21.9	28.3	45.8
Ours	Yes	**70.4**	**39.8**	40.8	**86.2**	**46.4**	**43.6**	**22.2**	**28.7**	**47.3**
Ours(SD)	Yes	71.0	40.2	41.4	86.4	46.9	43.9	22.3	29.1	47.7

Table 4. Efficiency Evaluation and Ablation Study of Post-processing Methods. Performance and computational efficiency across seven datasets without post-processing, conducted on a single RTX4090 24G GPU. The table compares various post-processing approaches: Trident SAM (from Trident(Shi et al., 2024)), Combination of Trident and CLIPer(Sun et al., 2024a) (Trident SAM+SD), and our speed-optimized version (Optimization SAM). The bottom rows present ablation experiments on Optimization SAM. Note: Coco-obj dataset experiments were omitted due to GPU memory constraints (24GB). Optimization SAM maintains the same core principles as Trident SAM.

Method	With background		Without background					Avg.	Total Time
	VOC21	Context60	VOC20	City	Context59	ADE	Stuff		
Main Methods									
Trident SAM+SD	**71.0**	**40.2**	**86.4**	**46.9**	**43.9**	**22.3**	**29.1**	**48.5**	–
Time	22min 2s	87min 44s	22min	41min 16s	88min 27s	29min 31s	93min 51s	–	384min 51s
Trident SAM	70.4	39.8	86.2	46.4	43.6	22.2	28.7	48.2	–
Time	2min 50s	20min 03s	2min 39s	6min 33s	20min 25s	5min 26s	24min 11s	–	82min 7s
Optimization SAM	70.4	39.8	86.2	46.4	43.6	22.2	28.7	48.2	–
Time	**2min 30s**	**19min 28s**	**2min 26s**	**5min 52s**	**19min 46s**	**4min 41s**	**22min 03s**	–	**76min 46s**
NO SAM	66.1	37.7	85.4	42.8	41.2	21.0	27.3	45.9	-
Time	1min 36s	15min 33s	1min 33s	4min 8s	15min 23s	2min 23s	16min 16s	-	56min 52s
Ablation Studies (based on Optimization SAM)									
w/o CCA	69.1	39.1	86.0	42.4	42.9	21.5	28.16	47.0	–
w/o box	65.7	38.0	84.7	42.9	41.4	21.3	27.2	46.0	–
w/o mask	**71.0**	39.7	86.1	46.2	**43.6**	**22.2**	**28.7**	**48.2**	–
full model	70.4	**39.8**	**86.2**	**46.4**	**43.6**	**22.2**	**28.7**	**48.2**	–

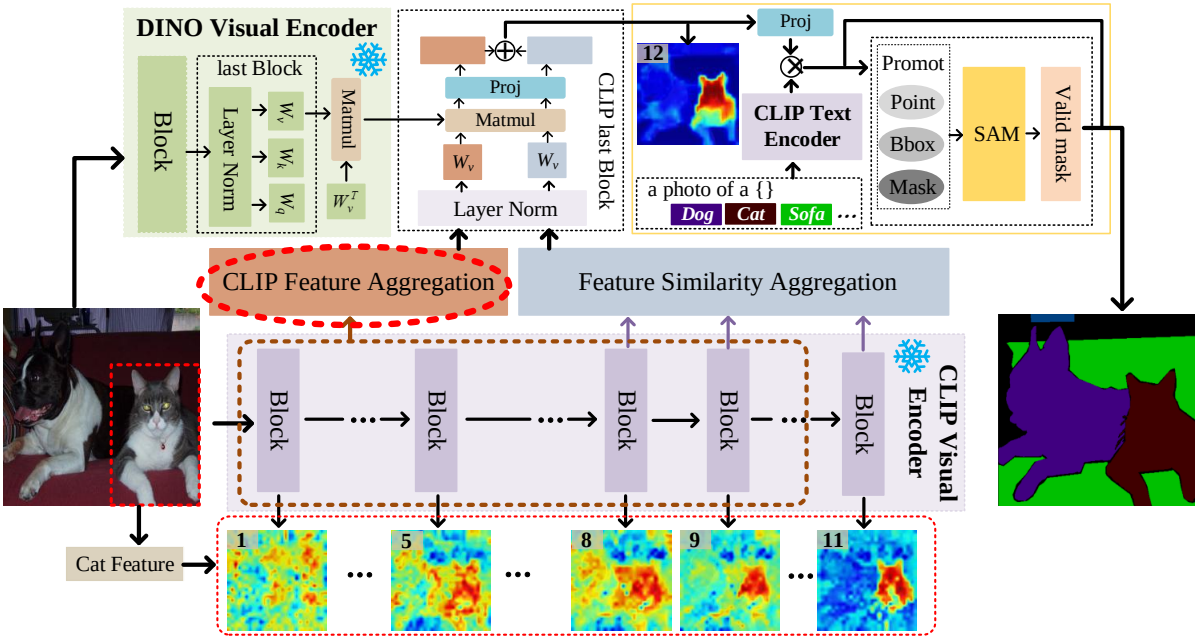

Figure 1. Overall architecture of the proposed S2CLIP. The framework consists of hierarchical progressive feature extraction from CLIP, feature fusion between CLIP and DINO, and SAM post-processing stage.

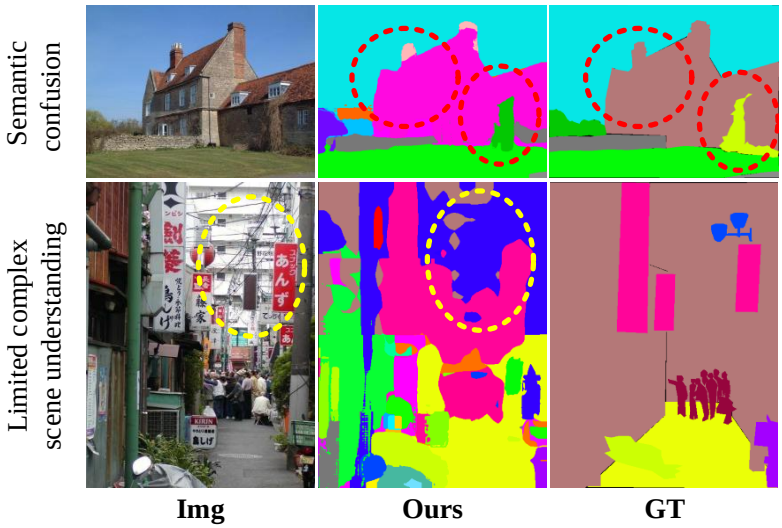

Figure 2. Failure Cases of S2CLIP. The upper section demonstrates semantic category confusion in S2CLIP, while the lower section illustrates that S2CLIP's understanding of extremely complex scenes requires further improvement.

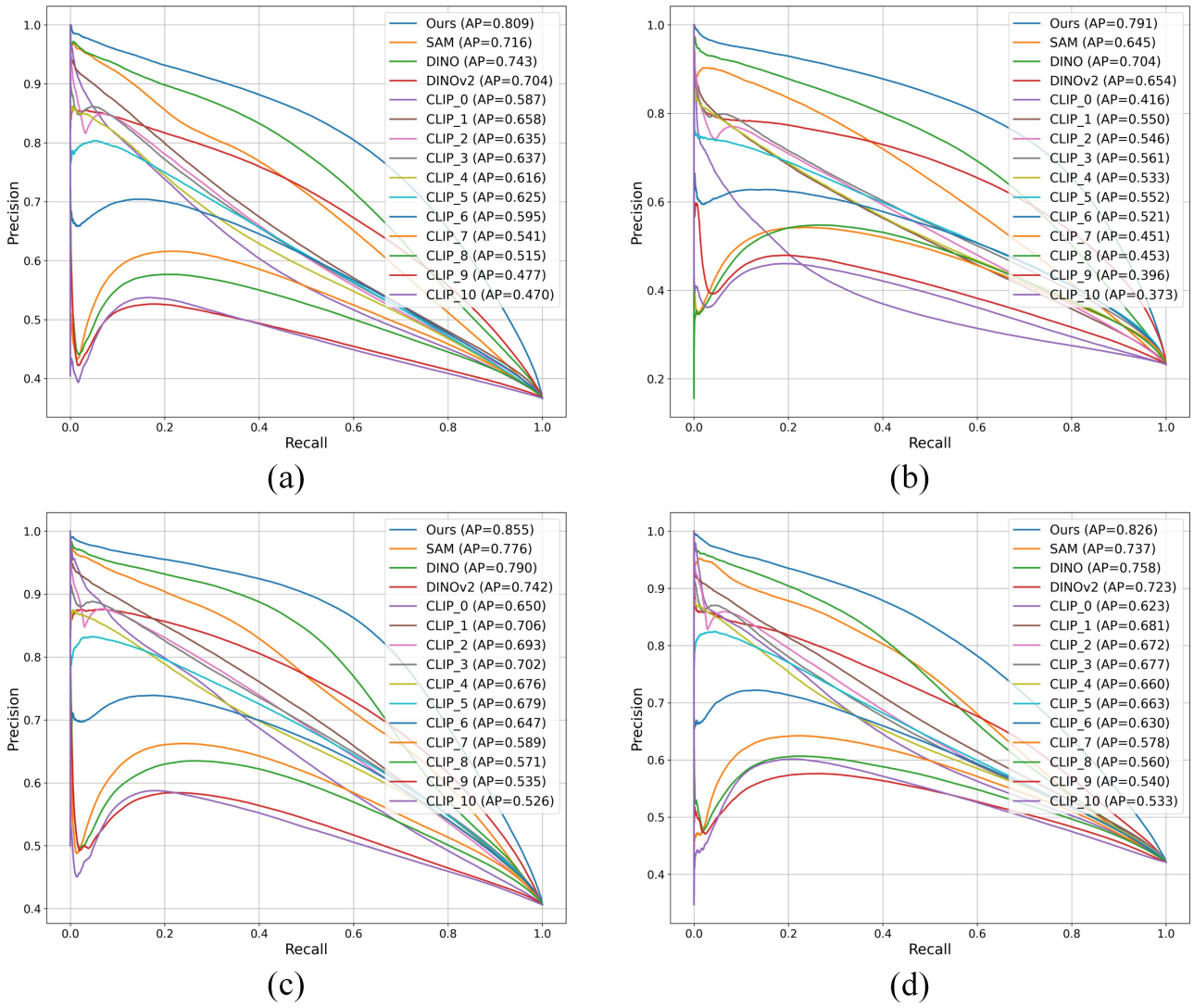

Figure 3. Precision-Recall Performance of Vision Foundation Models for Semantic Consistency Classification. Comparison of Average Precision (AP) between CLIP (layers 0-10) and other Vision Foundation Models (DINO, DINOV2, and SAM) across (a) ADE20K, (b) Cityscapes, (c) COCO-Stuff, and (d) Pascal Context datasets. Higher AP indicates better performance in distinguishing whether image patches belong to the same semantic category.

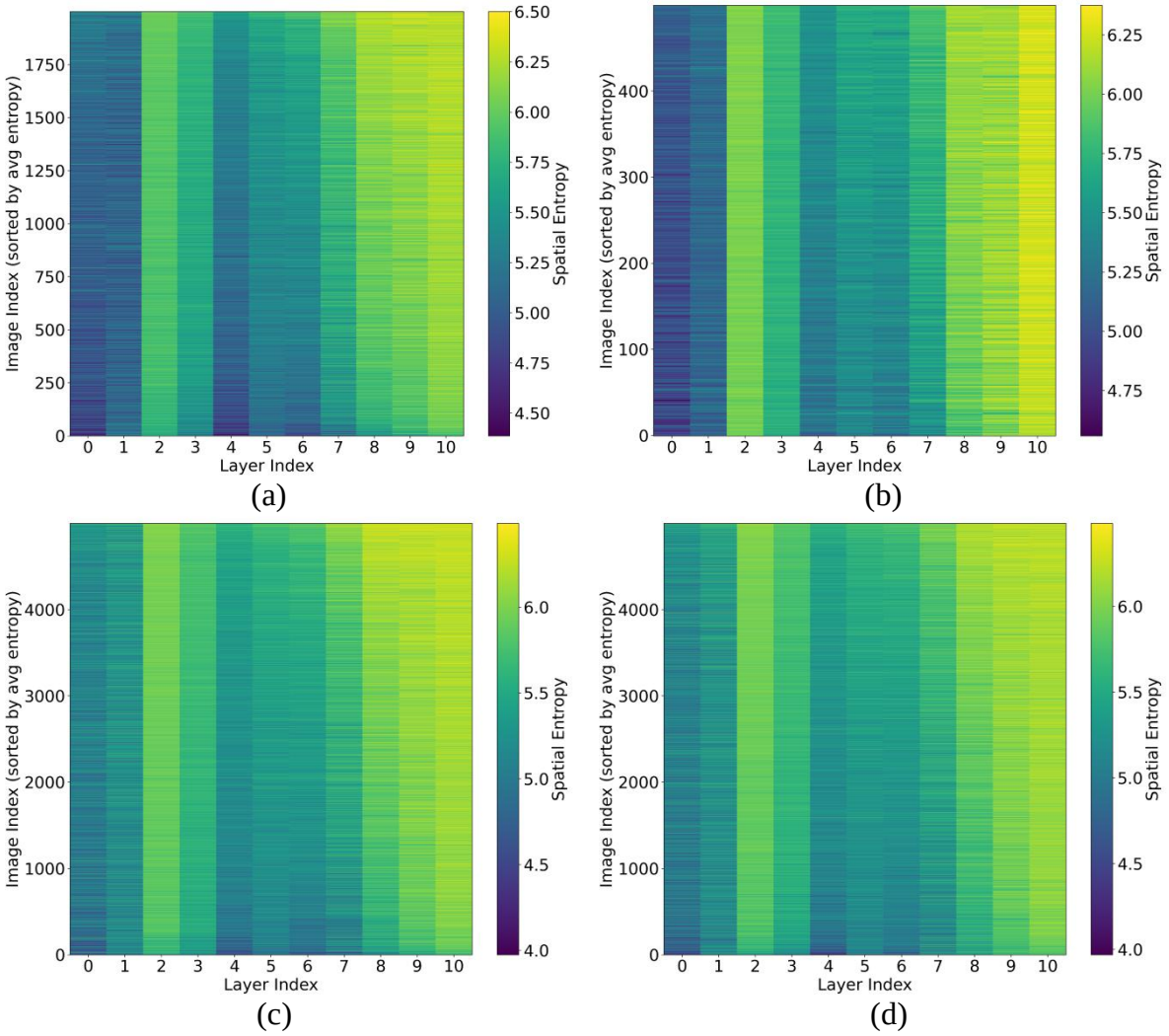

Figure 4. Spatial Entropy Distribution Across CLIP Layers on Multiple Datasets. Visualization showing spatial entropy values across CLIP layers for (a) ADE20K, (b) Cityscapes, (c) COCO-Stuff, and (d) Pascal Context datasets. Darker regions indicate lower spatial entropy. The spatial entropy computation methodology is described in Figure 8.

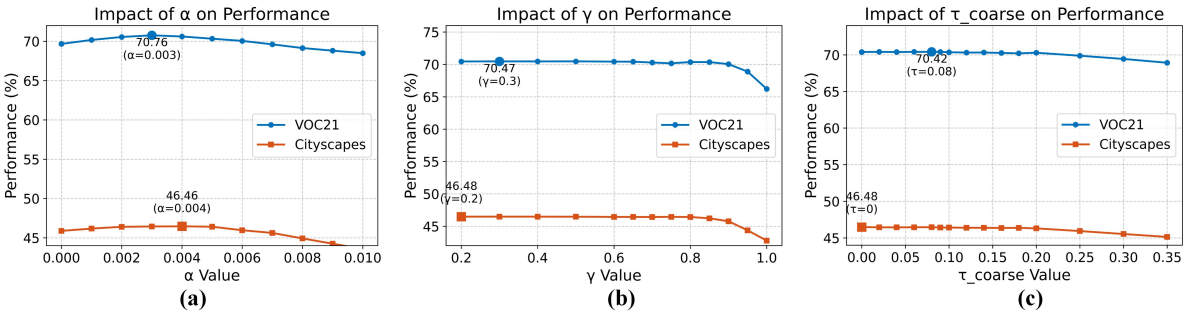

Figure 5. Overall architecture of the proposed S2CLIP. The framework consists of hierarchical progressive feature extraction from CLIP, feature fusion between CLIP and DINO, and SAM post-processing stage.

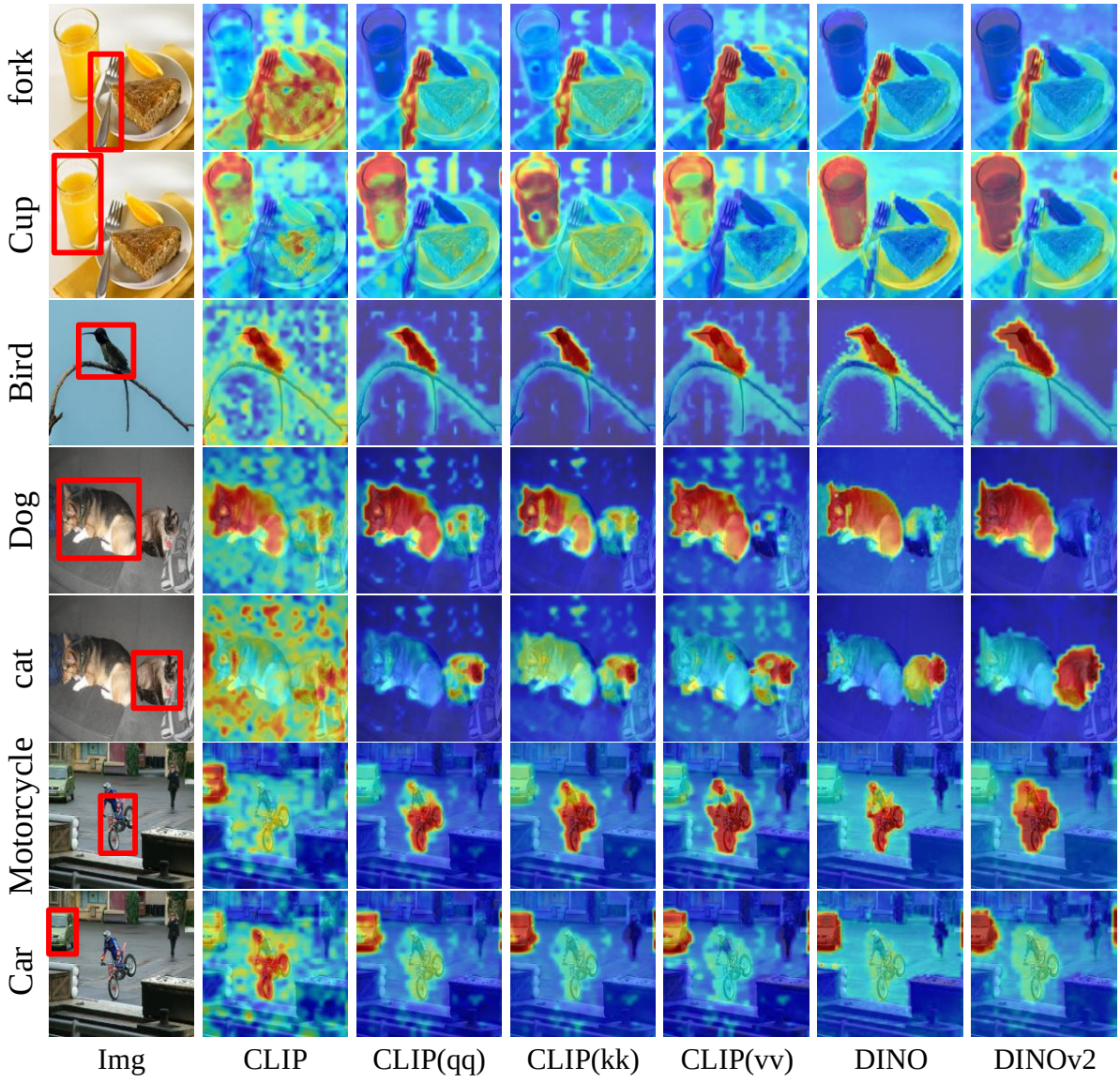

Figure 6. Feature Visualization Comparison of Vision Encoder Architectures. Qualitative comparison of features extracted by CLIP, DINO, and DINOV2 visual encoders. CLIP(qq), CLIP(kk), and CLIP(vv) represent different attention weight recombination strategies in CLIP's final layer.

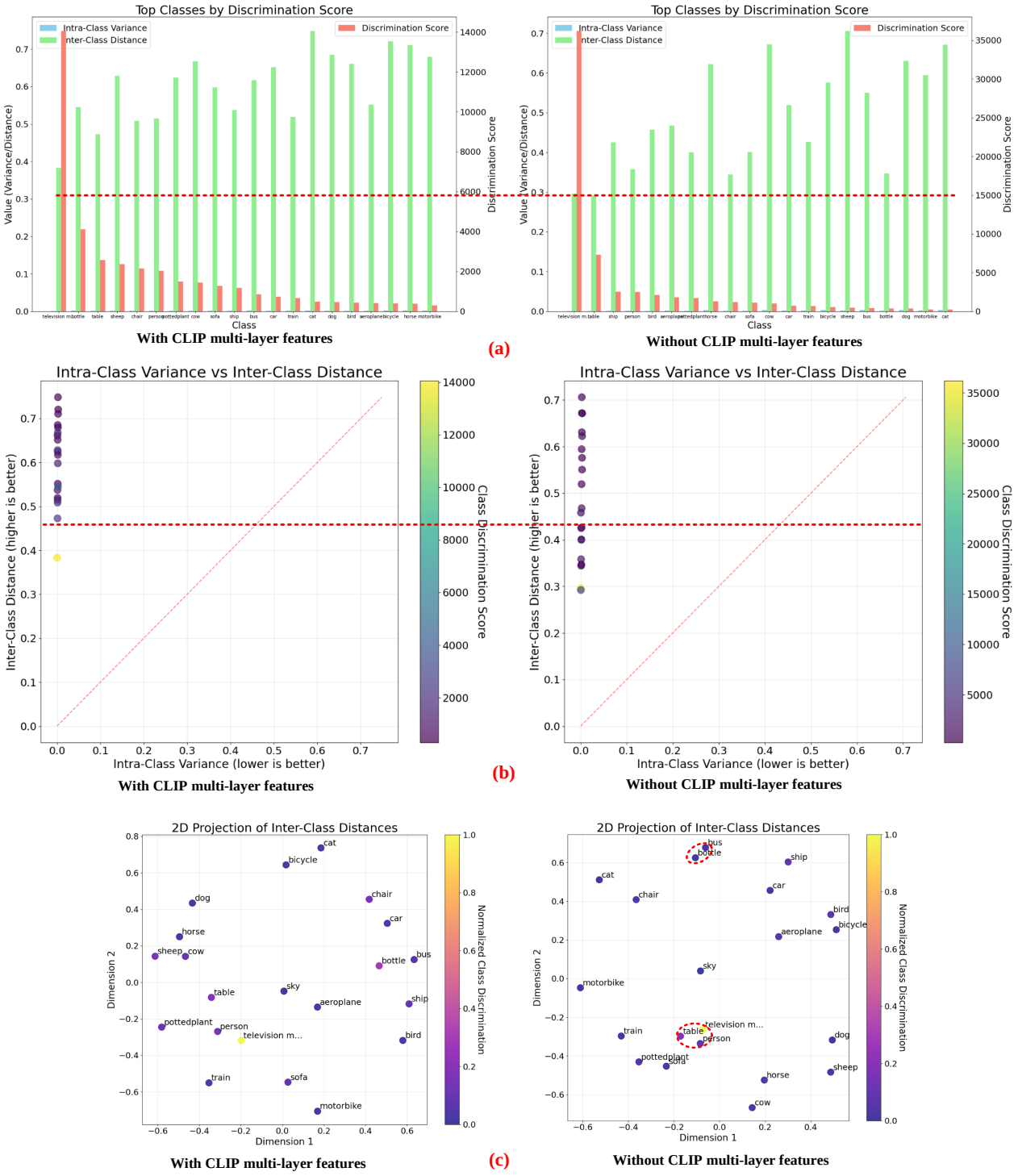

Figure 7. Analysis of intra-class variance and inter-class distance in feature distributions computed from segmentation outputs (without SAM). (a) Quantitative comparison where green bars represent inter-class distances (higher is better) and blue bars represent intra-class variance (lower is better). (b) Class scatter plot where the top-left region indicates desirable low intra-class variance (x-axis) and high inter-class distance (y-axis). (c) Projection of inter-class relationships where uniform distribution of points indicates good discriminability, while clustered points represent classes that are difficult to distinguish in feature space.

Algorithm 1 Spatial Entropy Calculation for Feature Maps

Input: $\mathbf{F} \in \mathbb{R}^{B\times C\times H\times W}$ {Feature map}

Preprocess and reshape $\mathbf{F}$ to $\mathbf{F} \in \mathbb{R}^{B\times C\times N}$ where $N = H \times W$ {N: spatial dimensions}

$\boldsymbol{\mu} \leftarrow \mathbb{E}[\mathbf{F}]_N$

$\boldsymbol{\sigma} \leftarrow \sqrt{\mathbb{V}[\mathbf{F}]_N}$

$\varepsilon \leftarrow \max(\min(\boldsymbol{\sigma}) \cdot 10^{-2}, 10^{-6})$

$\hat{\mathbf{F}} \leftarrow \frac{\mathbf{F}-\boldsymbol{\mu}}{\boldsymbol{\sigma}+\varepsilon}$

$\mathbf{F}^* \leftarrow \hat{\mathbf{F}} - \max(\hat{\mathbf{F}})_N$

$\mathbf{P} \leftarrow \frac{\exp(\mathbf{F}^*)}{\sum_{n=1}^{N} \exp(\mathbf{F}_n^*)+\varepsilon}$ {Normalized probability distribution}

$\mathbf{P} \leftarrow \frac{\max(\mathbf{P},\varepsilon)}{\sum_{n=1}^{N} \max(\mathbf{P}_n,\varepsilon)}$

$\mathbf{H} \leftarrow -\sum_{n=1}^{N} \mathbf{P}_n \log(\mathbf{P}_n)$ {Entropy per channel}

$\mathbf{P}_{sort} \leftarrow \text{sort}(\mathbf{P})_N$

$\mathbf{L} \leftarrow \text{cumsum}(\mathbf{P}_{sort})_N$

$\mathbf{G} \leftarrow 1 - \frac{2}{N} \sum_{i=1}^{N} \frac{i \cdot \mathbf{L}_i}{\sum_{j=1}^{N} \mathbf{P}_{sort,j}}$ {Gini coefficient}

$\boldsymbol{\rho} \leftarrow \mathbf{0}_B$ {Channel correlation}

if $C > 1$ **then**

  for $b = 1$ **to** B **do**

    $\mathbf{R}_b \leftarrow \text{corr}(\mathbf{P}_b)$

    $\boldsymbol{\rho}_b \leftarrow \frac{1}{C(C-1)} \sum_{i\neq j} \mathbf{R}_{b,i,j}$

  end for

end if

$\bar{H} \leftarrow \frac{1}{BC} \sum_{b=1}^{B} \sum_{c=1}^{C} \mathbf{H}_{b,c}$ {Mean spatial entropy}

if $\bar{H} \notin \mathbb{R}$ **then**

  $\bar{H} \leftarrow 0$

end if

Output: $\bar{H}$

Figure 8. Spatial Entropy Calculation for Feature Maps

Algorithm 2 Original Connected Component Analysis

Input: $\mathbf{S} \in \mathbb{R}^{C \times H \times W}$ {Segmentation mask}
Input: $\mathbf{L} \in \mathbb{R}^{C \times H \times W}$ {Segmentation logits}
Input: τ {Coarse threshold}
Input: $A_{\min}$ {Minimal area threshold}
Input: split_last $\in$ {True, False}

$\mathcal{R} \leftarrow \emptyset, \mathcal{B} \leftarrow \emptyset, \mathcal{S} \leftarrow \emptyset, \mathcal{P} \leftarrow \emptyset$
for $c \leftarrow 0$ **to** $C - 1$ **do**
  if $\neg$split_last $\wedge\ c = C - 1$ **then**
    continue
  end if
  $\mathcal{R}[c] \leftarrow \emptyset, \mathcal{P}[c] \leftarrow \emptyset, \mathcal{S}[c] \leftarrow \emptyset, \mathcal{B}[c] \leftarrow \emptyset$
  $\mathbf{M}_c \leftarrow \mathbf{S}[c]$ {Class mask}
  $\mathbf{L}_c \leftarrow \mathbf{L}[c]$ {Class logit}
  if $\max(\mathbf{L}_c) < \tau$ **then**
    continue
  end if
  $\mathbf{M}_{\text{labeled}} \leftarrow \mathcal{F}_{\text{label}}(\mathbf{M}_c, 2)$ {2-connected labeling}
  $N_{\text{regions}} \leftarrow \max(\mathbf{M}_{\text{labeled}})$
  for $r \leftarrow 1$ **to** N_{regions} **do**
    $\mathbf{M}_r \leftarrow \mathbb{I}[\mathbf{M}_{\text{labeled}} = r]$ {Region indicator mask}
    if $\sum_{i,j} \mathbf{M}_r[i,j] < A_{\min}$ **then**
      continue
    end if
    $s_r \leftarrow \frac{1}{|\Omega_r|} \sum_{(i,j) \in \Omega_r} \mathbf{L}_c[i,j]$ {Ω_r is region r}
    $\mathbf{L}_r \leftarrow \mathbf{L}_c \odot \mathbf{M}_r$
    $(i^*, j^*) \leftarrow \arg\max_{i,j} \mathbf{L}_r[i,j]$
    $\mathcal{P}[c] \leftarrow \mathcal{P}[c] \cup \{(j^*, i^*)\}$
    $\mathcal{R}[c] \leftarrow \mathcal{R}[c] \cup \{\mathbf{M}_r\}$
    $\mathcal{S}[c] \leftarrow \mathcal{S}[c] \cup \{s_r\}$
  end for
  if $|\mathcal{R}[c]| > 0$ **then**
    $\mathcal{R}[c] \leftarrow \text{stack}(\mathcal{R}[c])$ {Stack region masks}
    if $\mathcal{R}[c] = \emptyset$ **then**
      $\mathcal{B}[c] \leftarrow \mathcal{R}[c]$
    else
      $\mathcal{B}[c] \leftarrow \mathcal{F}_{\text{masks\_to\_boxes}}(\mathcal{R}[c])$
    end if
  end if
end for

Output: $\mathcal{R}, \mathcal{B}, \mathcal{S}, \mathcal{P}$ {Regions, boxes, scores, points}

Algorithm 3 Optimized Connected Component Analysis

Input: $\mathbf{S} \in \mathbb{R}^{C \times H \times W}$ {Segmentation mask}
Input: $\mathbf{L} \in \mathbb{R}^{C \times H \times W}$ {Segmentation logits}
Input: τ {Coarse threshold}
Input: $A_{\min}$ {Minimal area threshold}
Input: split_last $\in$ {True, False}

$\mathcal{R} \leftarrow \emptyset, \mathcal{B} \leftarrow \emptyset, \mathcal{S} \leftarrow \emptyset, \mathcal{P} \leftarrow \emptyset$
$\mathcal{D} \leftarrow \text{device}(\mathbf{L})$ {Device information}
$\mathbf{L}_{\max} \leftarrow \max_{h,w} \mathbf{L}_{c,h,w} \quad \forall c \in \{0, 1, \ldots, C-1\}$ {Class-wise max values}
$\mathcal{C}_{\text{valid}} \leftarrow \{c \mid \mathbf{L}_{\max}[c] \geq \tau\}$ {Pre-filter valid classes}
for $c \leftarrow 0$ **to** $C - 1$ **do**
  if $\neg$split_last $\wedge\ c = C - 1$ **then**
    continue
  end if
  $\mathcal{R}[c] \leftarrow \emptyset, \mathcal{P}[c] \leftarrow \emptyset, \mathcal{S}[c] \leftarrow \emptyset, \mathcal{B}[c] \leftarrow \emptyset$
  if $c \notin \mathcal{C}_{\text{valid}}$ **then**
    continue
  end if
  $\mathbf{M}_c \leftarrow \mathbf{S}[c]$ {Class mask (CPU memory)}
  $\mathbf{L}_c \leftarrow \mathbf{L}[c]$ {Class logit}
  $(\mathbf{M}_{\text{labeled}}, N_{\text{labels}}, \mathbf{\Gamma}) \leftarrow \mathcal{F}_{\text{CC}}(\mathbf{M}_c, 8)$ {8-connected components with stats}
  if $N_{\text{labels}} \leq 1$ **then**
    continue
  end if
  $\mathcal{V} \leftarrow \emptyset$ {Valid masks}
  for $r \leftarrow 1$ **to** $N_{\text{labels}} - 1$ **do**
    $\mathbf{M}_r \leftarrow \mathbb{I}[\mathbf{M}_{\text{labeled}} = r]$ {Region indicator mask}
    $A_r \leftarrow \mathbf{\Gamma}[r, \text{AREA}]$ {Region area from component stats}
    if $A_r < A_{\min}$ **then**
      continue
    end if
    $\mathbf{M}_r^{\mathcal{D}} \leftarrow \mathcal{F}_{\text{to\_device}}(\mathbf{M}_r, \mathcal{D})$ {Transfer to device}
    $s_r \leftarrow \frac{1}{|\Omega_r|} \sum_{(i,j) \in \Omega_r} \mathbf{L}_c[i,j]$ {Ω_r is region r}
    $\mathbf{L}_r \leftarrow \mathbf{L}_c \odot \mathbf{M}_r^{\mathcal{D}}$
    $(i^*, j^*) \leftarrow \arg\max_{i,j} \mathbf{L}_r[i,j]$
    $\mathcal{P}[c] \leftarrow \mathcal{P}[c] \cup \{(j^*, i^*)\}$
    $\mathcal{R}[c] \leftarrow \mathcal{R}[c] \cup \{\mathbf{M}_r\}$
    $\mathcal{S}[c] \leftarrow \mathcal{S}[c] \cup \{s_r\}$
    $\mathcal{V} \leftarrow \mathcal{V} \cup \{\mathbf{M}_r\}$ {Track valid masks}
  end for
  if $|\mathcal{R}[c]| > 0$ **then**
    $\mathcal{R}[c] \leftarrow \mathcal{F}_{\text{to\_device}}(\text{stack}(\mathcal{V}), \mathcal{D})$ {Stack valid masks}
    $\mathcal{B}[c] \leftarrow \mathcal{F}_{\text{masks\_to\_boxes}}(\mathcal{R}[c])$ {Convert masks to boxes}
  else
    $\mathcal{B}[c] \leftarrow \mathcal{R}[c]$ {Empty collection for invalid classes}
  end if
end for

Output: $\mathcal{R}, \mathcal{B}, \mathcal{S}, \mathcal{P}$ {Regions, boxes, scores, points}

Figure 9 Comparative Analysis of Trident CCA and Enhanced CCA Modules

Algorithm 4 Optimized SAM post-processing

Input: $\mathcal{I} \in \mathbb{R}^{H\times W\times 3}$, $\mathcal{S} \in \mathbb{Z}^{H\times W}$, $\mathcal{L} \in \mathbb{R}^{C\times H\times W}$, $C \in \mathbb{Z}^{+}$, $\mathcal{P}$
Output: $\mathcal{S}' \in \mathbb{Z}^{H\times W}$, $\mathcal{Q} \in \mathbb{R}^{N}$, $\mathcal{L}' \in \mathbb{R}^{C\times H\times W}$, $\mathcal{B}' \in \mathbb{R}^{N\times 4}$

$d \leftarrow \mathcal{S}$.device, $r \leftarrow 2$, $(h_d, w_d) \leftarrow (\lfloor H/r \rfloor, \lfloor W/r \rfloor)$
with no_grad() and mixed_precision(d):
$\mathcal{S}_d \leftarrow \mathcal{F}_{\text{down}}(\mathcal{S}, h_d, w_d)$, $\mathcal{L}_d \leftarrow \mathcal{F}_{\text{down}}(\mathcal{L}, h_d, w_d)$
if $\tau_c > 0$ **then**
  $\mathcal{S}_d[\max_c(\mathcal{L}_d) < \tau_c] \leftarrow C$, $\mathcal{M} \leftarrow \Phi(\mathcal{S}_d, C+1)$ {One-hot encoding}
else
  $\mathcal{M} \leftarrow \Phi(\mathcal{S}_d, C)$
end if
$\mathcal{M}_{\text{cpu}} \leftarrow \Pi_{\text{mem}}(\mathcal{M}, d)$, $(\mathcal{R}, \mathcal{B}, \mathcal{Q}_b, \mathcal{P}) \leftarrow$ SplitRegions$(\mathcal{M}_{\text{cpu}}, \mathcal{L}_d, \tau_c)$

if $\forall i \in [0, C) : |\mathcal{B}_i| = 0$ **then return** $(\mathcal{S}, \emptyset, \mathcal{L}, \emptyset)$
end if
  $b_{\text{size}} \leftarrow \min(32, \max(1, \lfloor M_{\text{free}}/(3 \cdot 10^9) \rfloor))$, $\mathcal{P}$.PrecomputeTransforms(h_d, w_d, H, W)
  $\mathbb{I} \leftarrow \emptyset$, $\mathcal{B}_c, \mathcal{M}_v, \mathcal{Q}_v, \mathcal{L}_v, \mathcal{R}_f \leftarrow \emptyset, \emptyset, \emptyset, \emptyset, \emptyset$ {Collections init}
  for $i \in [0, C)$ **do**
    if $|\mathcal{R}_i| > 0$ **then**
      $(h_n, w_n) \leftarrow \mathcal{P}$.GetPreprocessShape$(H, W, 256)$, $\mathcal{L}_r^i \leftarrow \mathcal{F}_{\text{resize}}(\mathcal{L}_d[i], h_n, w_n)$
      $\mathcal{L}_r^i \leftarrow \mathcal{F}_{\text{pad}}(\mathcal{L}_r^i, 256 - w_n, 256 - h_n) \cdot \tau_m \cdot \mathbb{I}_{\{\mathcal{L}_r^i > \tau_c\}}$
      $\mathcal{B}_t^i \leftarrow \mathcal{P}$.TransformBoxes$(\mathcal{B}_i, h_d, w_d)$, $\mathcal{P}_t^i \leftarrow \mathcal{P}$.TransformPoints$(\mathcal{P}_i, h_d, w_d)$
      $\mathbb{I} \leftarrow \mathbb{I} \cup \{(i, \mathcal{B}_t^i, \mathcal{P}_t^i, \mathcal{L}_r^i, \mathcal{R}_i, \mathcal{B}_i, \mathcal{P}_i)\}$
    end if
  end for

  for $j \leftarrow 0$ **to** $|\mathbb{I}|$ **step** b_{size} **do**
    $\mathbb{I}_j \leftarrow \mathbb{I}[j : j + b_{\text{size}}]$
    for each $(i, \mathcal{B}_t^i, \mathcal{P}_t^i, \mathcal{L}_r^i, \mathcal{R}_i, \mathcal{B}_i, \mathcal{P}_i) \in \mathbb{I}_j$ **do**
      $(\mathcal{M}_i, \mathcal{Q}_i, \mathcal{L}_i) \leftarrow \mathcal{P}$.Predict$(\mathcal{P}_t^i, \mathbf{1}, \mathcal{B}_t^i, \mathcal{L}_r^i)$, $\mathcal{V}_i \leftarrow \{\mathcal{Q}_i > \tau_{iou}\}$
      if $|\mathcal{V}_i| < |\mathcal{R}_i|$ **then** $\mathcal{R}_f \leftarrow \mathcal{R}_f \cup \{\mathcal{R}_i[\neg\mathcal{V}_i]\}$
      end if
      if $|\mathcal{V}_i| > 0$ **then** $\mathcal{M}_v \leftarrow \mathcal{M}_v \cup \{\mathcal{M}_i[\mathcal{V}_i]\}$, $\mathcal{Q}_v \leftarrow \mathcal{Q}_v \cup \{\mathcal{Q}_i[\mathcal{V}_i]\}$, $\mathcal{L}_v \leftarrow \mathcal{L}_v \cup \{\mathcal{L}_i[\mathcal{V}_i]\}$, $\mathcal{B}_c \leftarrow \mathcal{B}_c \cup \{\mathcal{B}_i[\mathcal{V}_i]\}$
      end if
    end for
  end for
  if $|\mathcal{B}_c| > 0$ **then**
    with mixed_precision(d):
    $\mathcal{M}_{all} \leftarrow$ Concat$(\mathcal{M}_v)$, $\mathcal{Q}_{all} \leftarrow$ Concat$(\mathcal{Q}_v)$, $\mathcal{L}_{all} \leftarrow \mathcal{P}$.PostprocessMasks(Concat$(\mathcal{L}_v), H, W)$
    $\mathcal{B}_{all} \leftarrow$ Concat$(\mathcal{B}_c) \cdot r$, $(\mathcal{S}', \mathcal{L}') \leftarrow$ MapRefinement$(\mathcal{M}_{all}, \sigma(\mathcal{L}_{all}), \mathcal{B}, \mathcal{L})$
    $\mathcal{S}' \leftarrow \mathcal{S}' \cdot \mathbb{I}_{\{\sum_c \mathcal{L}'_c > 0\}} + \mathcal{S} \cdot \mathbb{I}_{\{\sum_c \mathcal{L}'_c = 0\}}$
    if $|\mathcal{R}_f| > 0$ **then** $\mathcal{R}_f \leftarrow$ Resize(Concat$(\mathcal{R}_f), H, W)$, $(\mathcal{S}', \mathcal{L}') \leftarrow$ MapFailedRegions$(\mathcal{S}', \mathcal{L}', \mathcal{R}_f, \mathcal{L}, \mathcal{S})$
    end if
    return $(\mathcal{S}', \mathcal{Q}_{all}, \mathcal{L}', \mathcal{B}_{all})$
  else
    return $(\mathcal{S}, \emptyset, \mathcal{L}, \emptyset)$
  end if

Figure 10. Architectural Distinctions Between Trident SAM and Optimized SAM