Ultra High Resolution in CVPR2022

Speaker: Gong, Qiqi

Outline

- Introduction to Ultra High Resolution
- Method Summary
- Paper Sharing
- Inspiration

Introduction to UHR (Ultra high resolution,超高分辨率)

- Semantic Segmentation Dataset Comparison

Name	Train #	Val #	Test #	Class #	Resolution
Pascal VOC	1,464	1,449	-	21	<1000
COCO	118K	5K	41K	91	640 X 480
ADE20K	20K	2K	3K	150	<1024 x 768
Cityscapes	2975	500	1525	20	1024 X 2048
Mapillary Vistas	18K	2K	5K	124	1024*768~4000*6000
BIG	-	-	-	-	2048×1600~5000×3600
UHRSD	4932	988	-	-	4K~8K

Method Summary

- Background: Development of collecting devices brings UHR images
- Fundamental Problems
  - Two obstacles: Computation & Memory
  - Receptive field
  - Downsampling

Method Summary

- Multi-scale Decoder
  - GLNet (CVPR2019)
  - CascadePSP (CVPR2020)
- Boundary Refinement
  - BASNet (CVPR2019)
  - DeepStrip (CVPR2020)
  - SegFix (ECCV2020)
  - PointRend (ECCV2020)
- Bi-path
  - PGNet (CVPR2022)
  - ISDNet (CVPR2022)

Paper Sharing——PGNet

Pyramid Grafting Network for One-Stage High Resolution Saliency Detection

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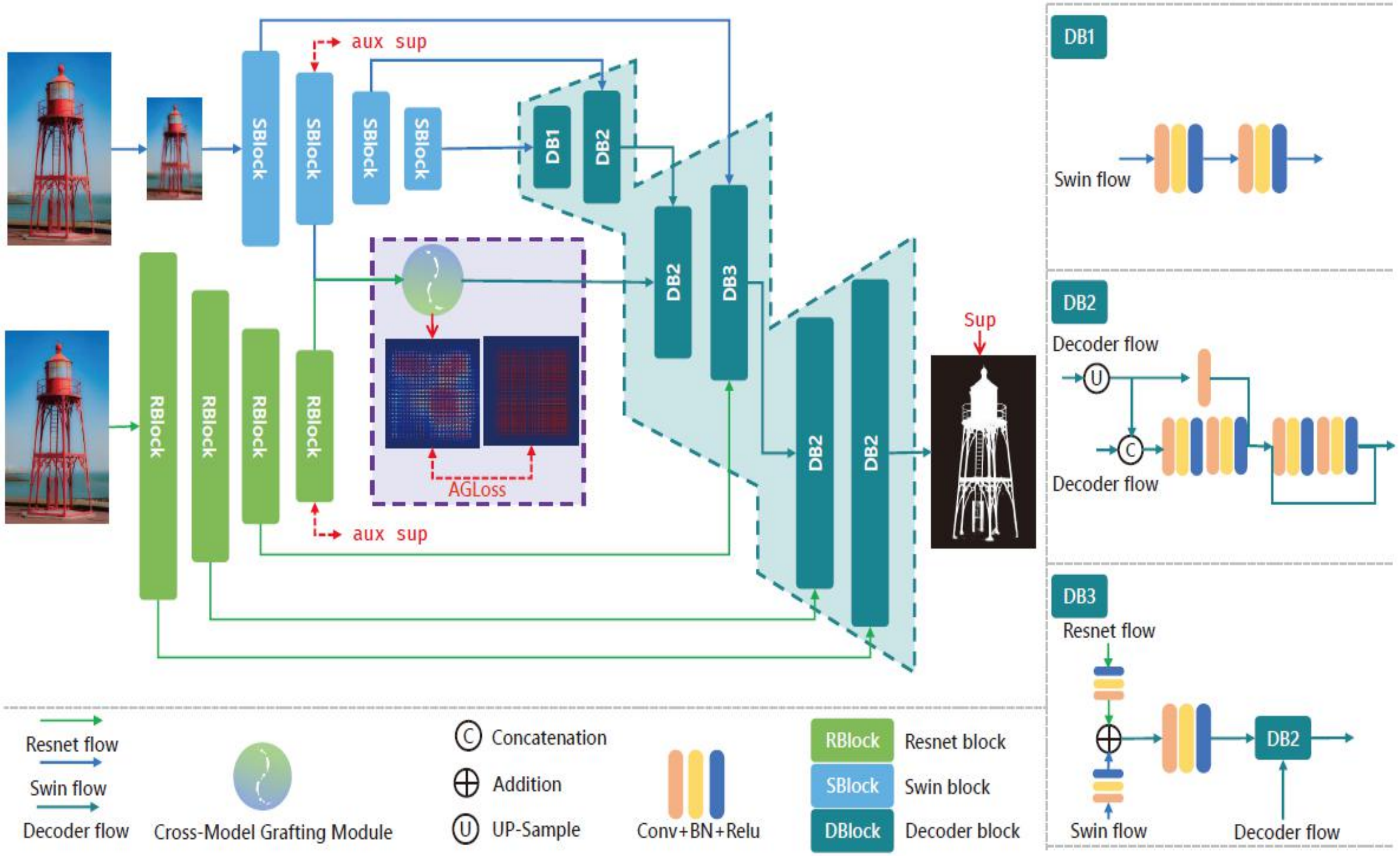
PGNet

- Motivation
  - Transformer encoder performs well in LR cases
  - CNN encoder performs well in HR cases
- Key point: How to fuse information from different encoders?

PGNet



aux sup
SBlock
SBlock
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SBlock
DB1
DB2
DB2
DB3
DB2
DB2
Sup
RBlock
RBlock
RBlock
RBlock
AGLoss
aux sup
DB1
Swin flow
DB2
Decoder flow
U
C
Decoder flow
DB3
Resnet flow
DB2
Swin flow
Decoder flow
Resnet flow
Swin flow
Decoder flow
Cross-Model Grafting Module
C Concatenation
Addition
U UP-Sample
Conv+BN+Relu
RBlock Resnet block
SBlock Swin block
DBlock Decoder block

PGNet

- Cross Model Grafting (融合) Module

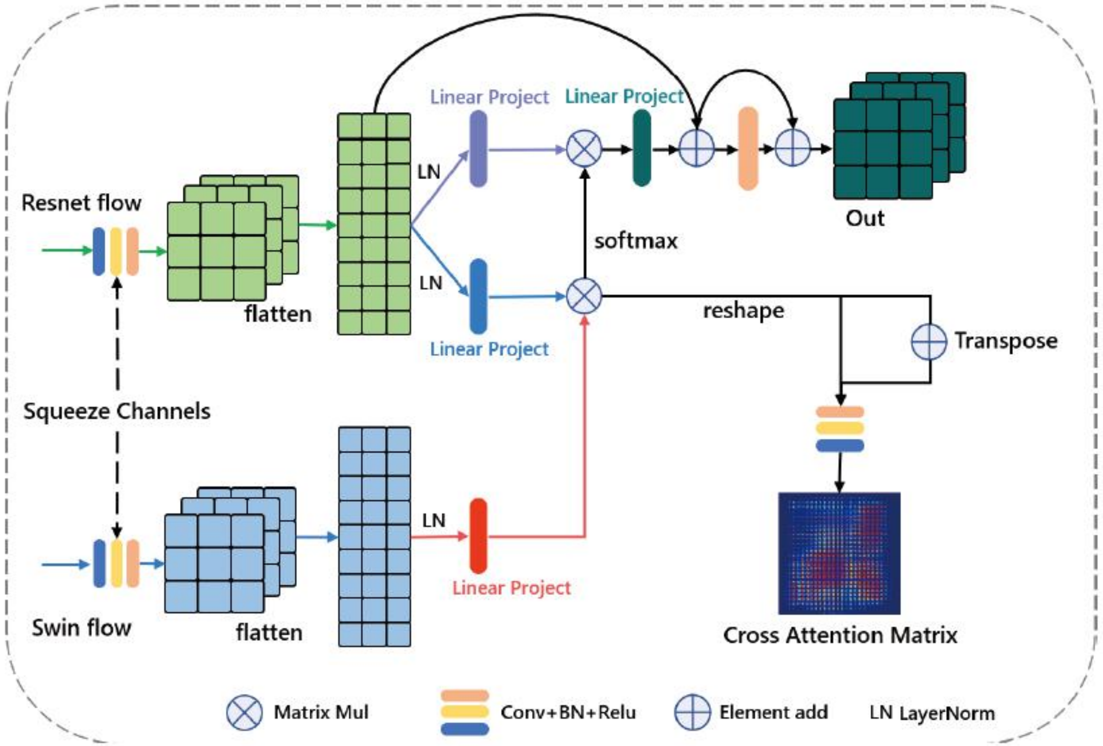
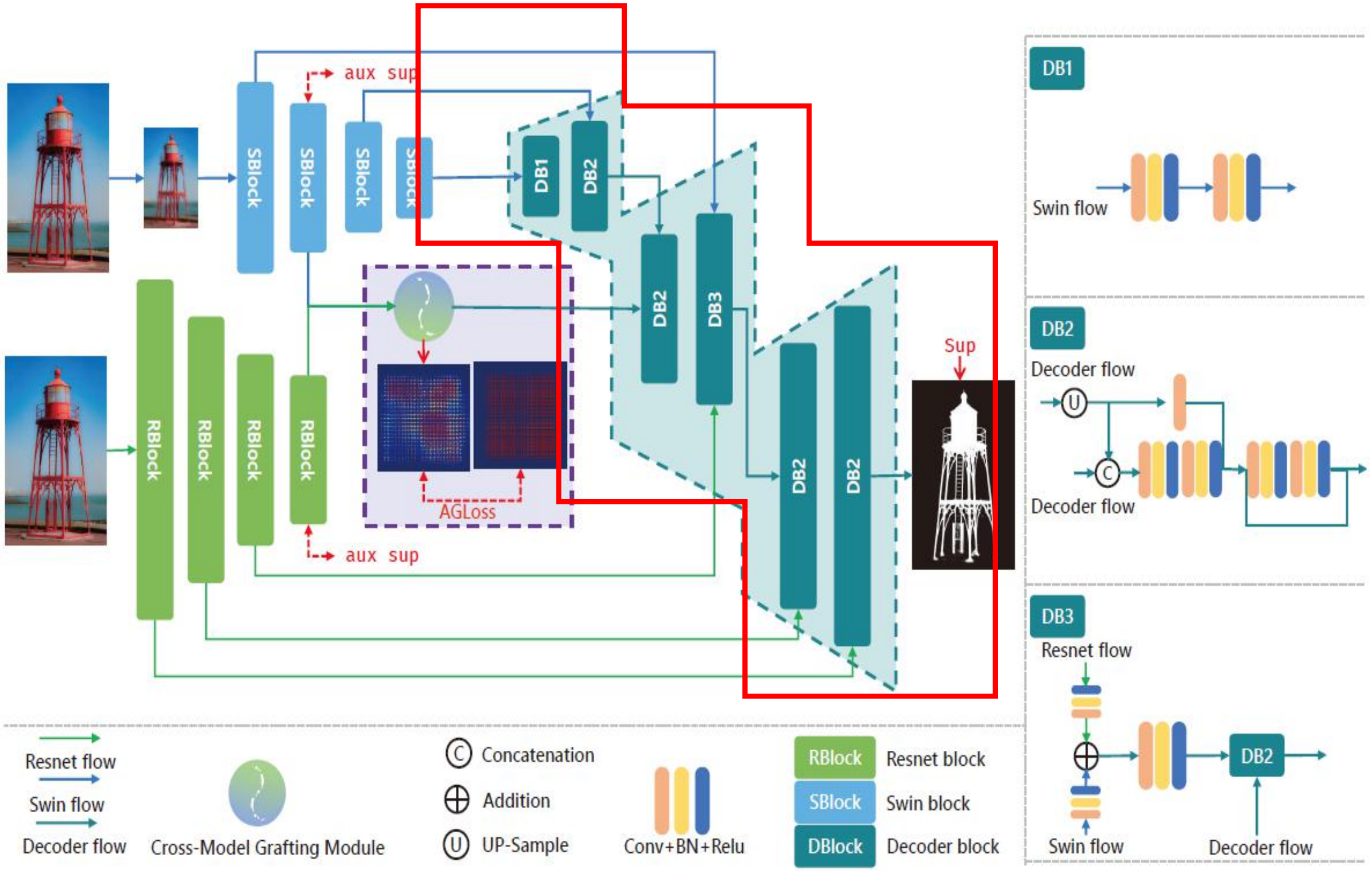


Figure 5. Architecture of Cross-Model Grafting Module.

PGNet

- Decoder



ISDNet

ISDNet: Integrating Shallow and Deep Networks for Efficient Ultra-high Resolution Segmentation

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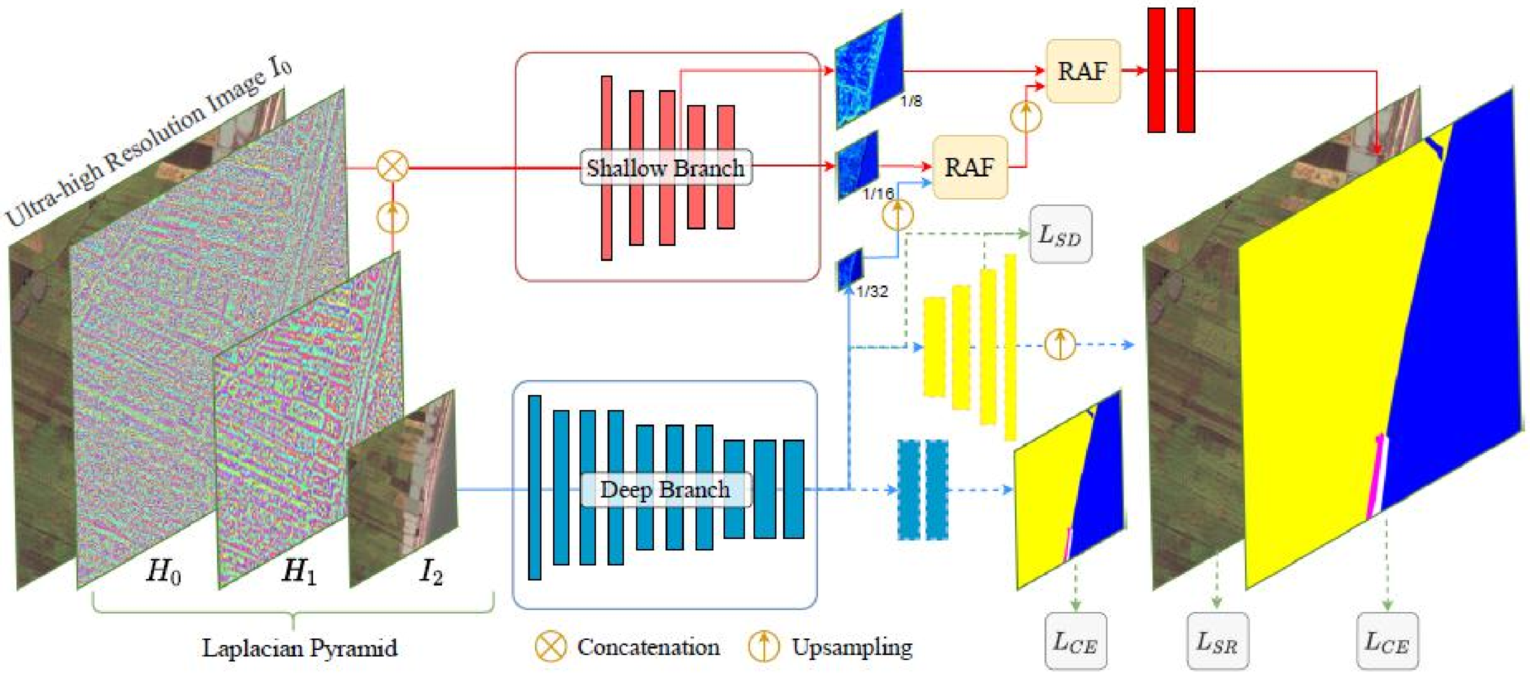
ISDNet

- Summary
  - Bilateral path (shallow + deep)
  - Relation-Aware feature Fusion mechanism (RAF)
  - **Super-resolution aux loss**
- Motivation
  - Trade-off among accuracy, speed and memory for UHR sem_seg

Method	mIoU ↑	FPS ↑	Memory(MB) ↓
Generic Methods			
BiSeNetV1 [37]	74.44	42.43	2147
BiSeNetV2 [36]	75.80	43.07	1602
PSPNet [40]	74.87	15.15	1584
ICNet [39]	74.43	**68.55**	**1390**
STDC [11]	74.5	62.15	1536
DeepLabv3 [1]	**76.70**	13.32	1468
UHR Methods			
DenseCRF [21]	62.95	0.04	1575
DGF [32]	63.33	3.13	1727
SegFix [38]	65.83	2.63	2033
PointRend [20]	64.39	7.14	2052
MagNet [18]	67.57	0.34	2007
MagNet-Fast [18]	66.91	3.13	2007
Ours (ISDNet)	**76.02**	**50.79**	**1510**

Table 3. Segmentation results on the CityScapes dataset. We evaluate the speed and memory under our environment, and the accuracy of UHR competitors are collected from [18].

ISDNet

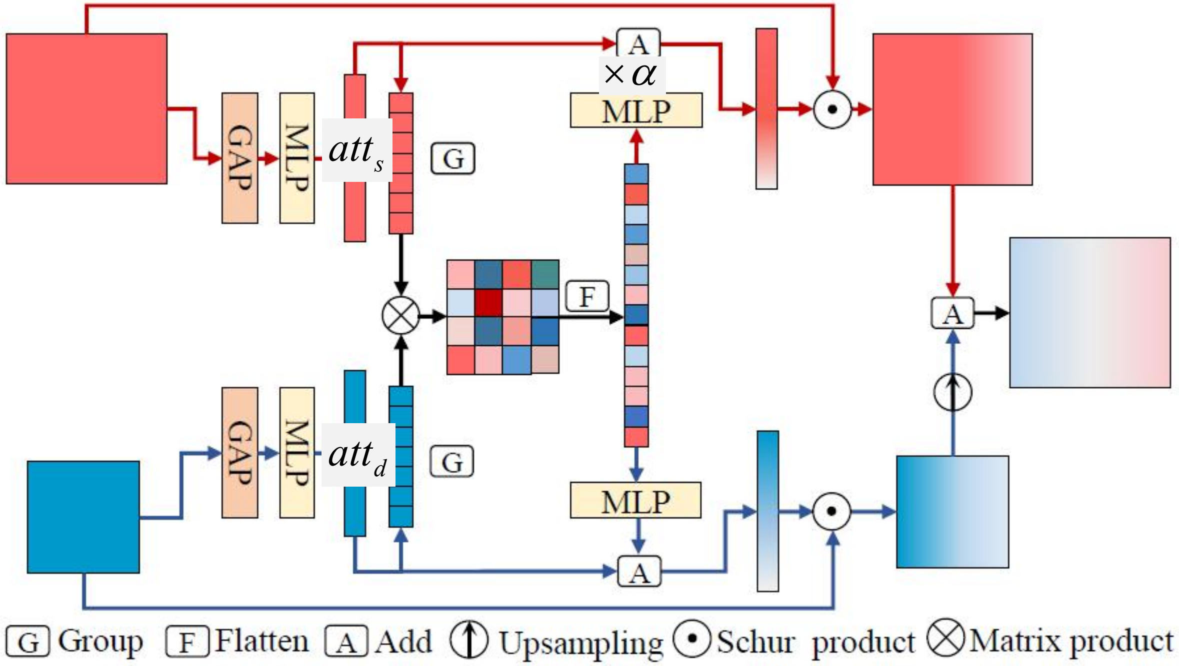


$$H_i = g_i(I) - \text{Upsample}\left(g_{i+1}(I)\right), \qquad (1)$$

where I represents the full scale image, $g(.)$ denotes guassian blur and i is the number of levels in the pyramid.

*STDC: 《Rethinking BiSeNet for Real-time Segmentation》--2021CVPR

ISDNet--RAF



ADD	CAT	CW	M_s	M_d	mIoU	FPS	Mem(MB)
✓			-	-	72.20	31.69	-
✓		✓	-	-	72.42	29.73	1891
	✓		-	-	71.88	23.98	-
	✓	✓	-	-	72.57	25.76	2204
✓		✓	✓		72.63	28.93	-
✓		✓	✓	✓	73.30	27.70	1948

Table 6. Comparison of feature fusion methods. ADD and CAT represent two simple fusion strategies: addition and concatenation. CW means channel-wise attention mechanism. M_s and M_d denote the relation-aware attention for deep and shallow branch.

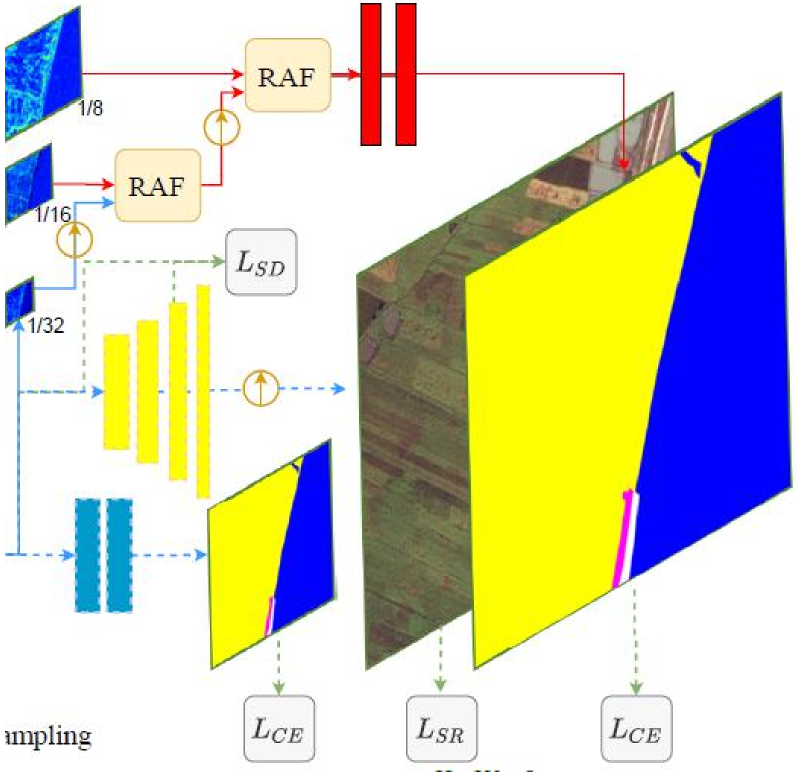
ISDNet--Loss

- Final Segmentation loss: L_{SEG}
- Deep branch aux loss: L_{AUX}
- Super-resolution loss: $L_{SR} = \left\| I_0 - I_{rec} \right\|_2^2$
- Structure distillatoin loss:

$$\mathcal{L}_{SD} = \left\| F_d^T F_d - F_{sr}^T F_{sr} \right\| .$$

Baseline	$\mathcal{L}_{SR}$	$\mathcal{L}_{SD}$	H	mIoU
✓				72.31
✓	✓			72.55
✓	✓	✓		72.70
✓	✓	✓	✓	73.30

Table 7. Comparison of loss components and heterogeneous input. H indicates high-frequency residual inputs for the shallow branch.



ISDNet--Ablation on Cityscapes

Method	mIoU	FPS	Mem(MB)
PSPNet [40]	74.87	15.15	1584
PSPNet [40] (½ scale)	72.87	54.99	1160
PSPNet [40] (¼ scale)	65.20	169.91	1076
PSPNet [40] + ISD	74.30	58.29	1540
Segformer-b0 [35]	73.45	13.70	3114
Segformer-b0 [35] (½ scale)	71.20	65.49	1174
Segformer-b0 [35] (¼ scale)	51.19	76.22	1032
Segformer-b0 [35] + ISD	72.99	41.82	1500

Table 4. Comparison of existing models integrating with our framework. We evaluate the corresponding methods with different scales to compare the accuracy and inference cost.

Inspiration

- CNN + Transformer structure
- Bi-path structure