SC-CrackSeg: A Real-time Shared Feature Pyramid Network for Crack Detection and Segmentation

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Overview of key contributions

Our key contributions are:

- Introduce a new state-of-the-art model specifically designed for crack segmentation application task
- Assessed the unexplored field of domain adversarial semantic segmentation using transfomer models
- Evaluated lightweight segmentation transformers for unsupervised domain adaptation, and introduced novel pseudo-teacher approach for state-of-the-art results

Crack Segmentation

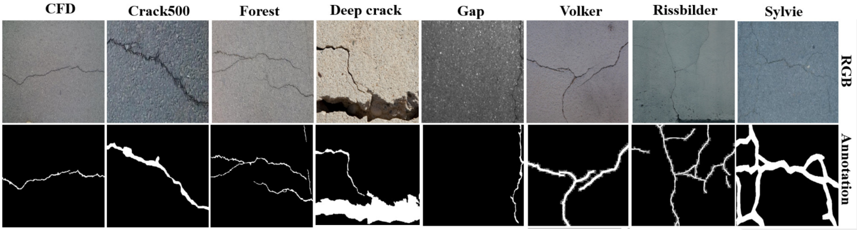

Figure: Crack dataset samples

Our Architecture

a)

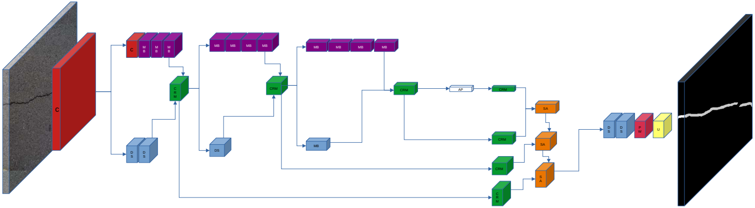

Figure: SC-CrackSeg

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SDDNet

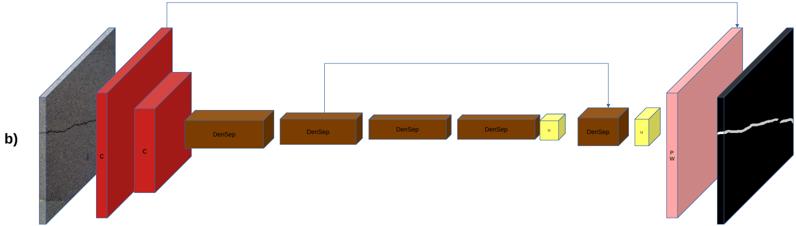

Figure: SC-CrackSeg

SC-CrackSeg (Modified)

c)

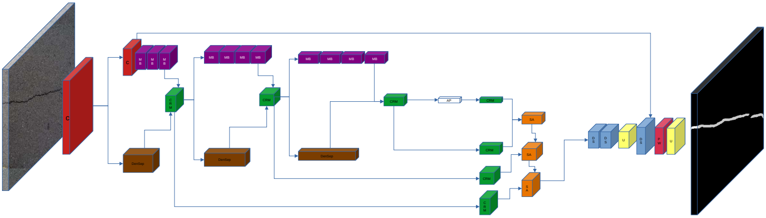

Figure: SC-CrackSeg

Final Results

	U-Net	SDDNet	SC-CrackSeg	SCMNet	SC-CrackSeg-1	SC-CrackSeg-2	SC-CrackSeg-3	SC-CrackSeg-4
Parameters	0.35M	**0.33M**	1.27M	1.26M	0.63M	1.01M	1.51M	1.3M
FLOPs	2.44G	2.75G	1.4G	1.62G	18.12G	**1.24G**	2.16G	4.32G
Crack Test Set Performance (% mIoU)	0.796	**0.815**	0.807	0.81	0.63	0.808	0.812	0.803
FPS	**27.05**	15.84	15.94	16.87	12.75	15.87	14.01	13.15

Table: Performance evaluation of modifications (and SDDNet) on Crack Test set.

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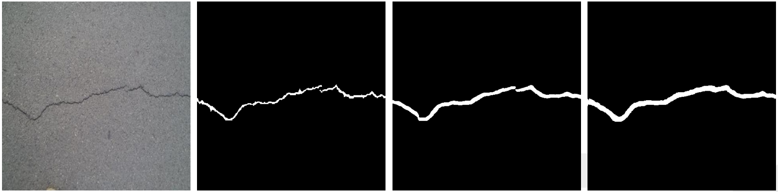
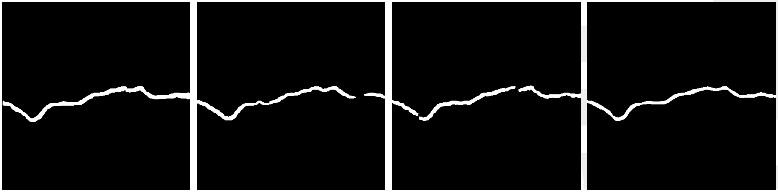
Qualitative Results



(a) Source (b) Ground Truth (c) SDDNet (d) U-Net



(e) SC-CrackSeg (f) SC-CrackSeg-2 (g) SC-CrackSeg-3 (h) SC-CrackSeg-4

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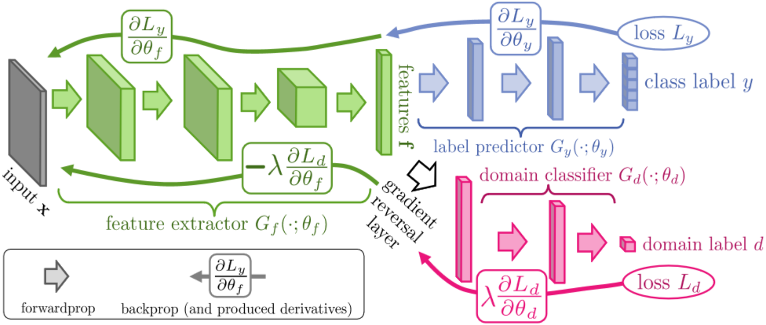
Domain Adversarial Training



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Issue with Segmentation Transformers

Model	mIoU (source-only)	mIoU (with discriminator)	Relative Change
DeelabV3+ (ResNet-50)	33.9	35.97	+2.07
SegFormer (MiT-B3)	41.78	39.38	-2.40

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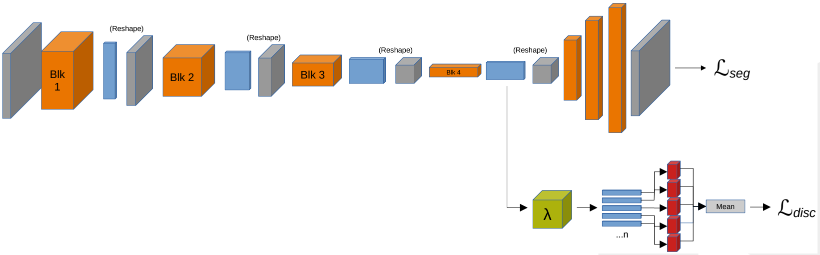
DAS Patchwise Architecture



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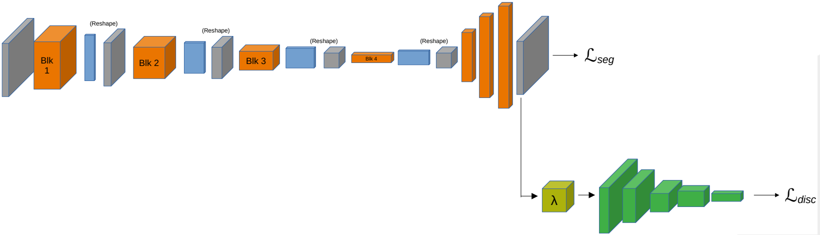
DAS DCGAN Architecture



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Final Best Results

Auxiliary Method	Discriminator	mIoU
RCS	DCGAN	**44.76**
Class distribution matching	DCGAN	39.4
Fine class matching	DCGAN	37.22
Source-Only	-	41.78

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Final Best Results

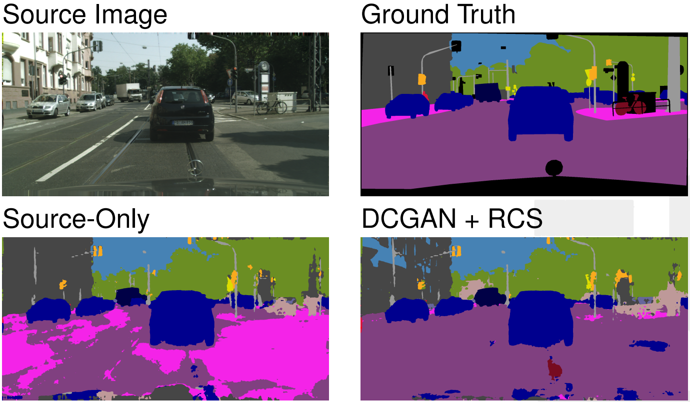

Figure: Comparison of DCGAN + RCS DAS against source-only training.

Baseline Comparison

Model	Reported Params	Measured Params (M)	Reported FLOPs (GFlops)	Measured FLOPs (GFlops)	mIoU (Source-Only)	mIoU (UDA)
Fast-SCNN	1.11M	1.46	-	**0.94**	20.95	-
Segformer(MiT-B0)	3.8M	6.09	8.4	42.94	26.57	47.55
DAFormer (MiT-B0)	-	4.26	-	17.69	28.12	**50.56**
MobileViT (Small)	6.4 M	12.65	-	16.93	31.86	46.73
MobileViT (XX-Small)	-	6.28	-	7.08	30.35	41.38
TopFormer (Base)	5.1M	1.81	2.7	5.06	**33.32**	43.15
TopFormer (Tiny)	1.4M	**1.39**	-	0.58	27.78	36.98

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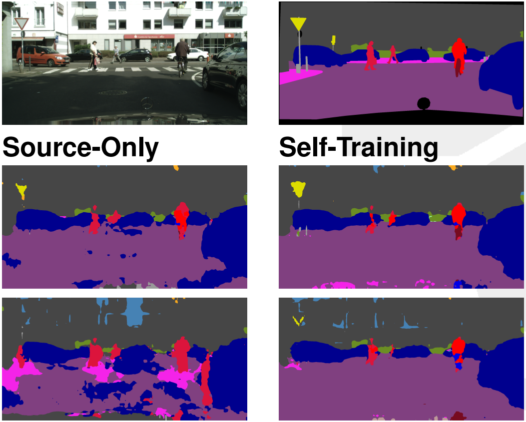
Baseline Qualitative Comparison

Ground Truth

Model | **Source-Only** | **Self-Training**

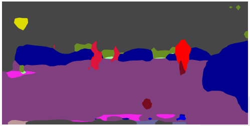
Topformer-Base

Topformer-Tiny



Baseline Qualitative Comparison

MobileViT-Small



MobileViT-XX-Small

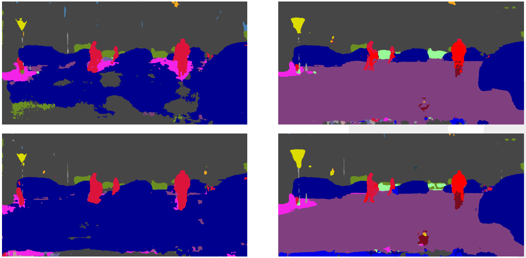
Fast-SCNN

N/A

Baseline Qualitative Comparison

SegFormer-B0

DAFormer-B0



Pseudo-Teacher UDA

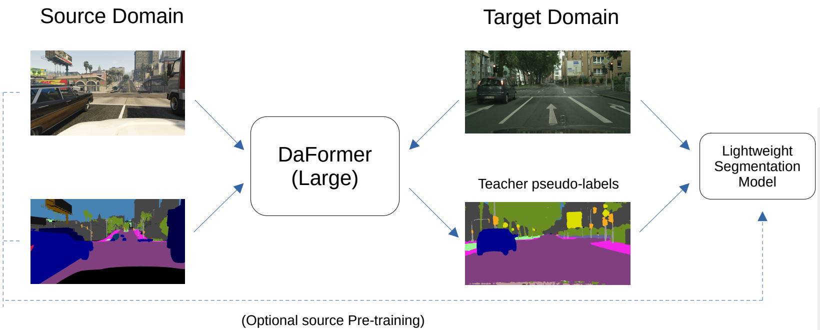


Figure: The pseudo-teacher pipeline.

Pseudo-Teacher UDA Results (GTA Dataset)

Model	UDA Approach	Source-Only	With UDA	Oracle	Relative Performance
TopFormer-Base	Pseudo-Teacher	**33.32**	**61.18**	66.56	91.92%
TopFormer-Tiny	Pseudo-Teacher	27.78	56.26	59.39	**94.73%**
DAFormer (MiT-B0)	Self-Training	28.12	47.55	**70.78**	67.18%

Pseudo-Teacher Qualitative Results (GTA Dataset)

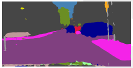
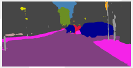
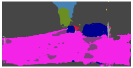
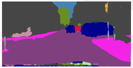
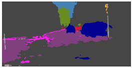
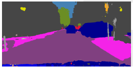
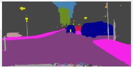
Ground Truth				
Model	**Approach**	**Source-Only**	**UDA**	**Oracle**
Topformer-Base	Pseudo-Teacher			
Topformer-Tiny	Pseudo-Teacher			
DAFormer	Pseudo-Teacher			

Table: Qualitative results of Pseudo-Teacher approach on Cityscapes dataset.

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Thank you!

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