Semantic Segmentation of Indian Road Scenes using Unsupervised Domain Adaptation

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Contents

Introduction

- Semantic segmentation is a **computer vision** technique that aims to segment an image into different regions based on the semantic meaning of the objects present in the image.

- The goal is to identify and **label each pixel** in an image with a corresponding class label, such as person, car, tree, or sky.

- Semantic segmentation has various applications, including object detection, scene understanding, medical imaging, and **autonomous driving**.

- It is required for self-driving cars to accurately identify objects on the road, such as cars, pedestrians, and traffic signs, to make **real-time decisions** for safe navigation.

Related Works

- **Unsupervised Domain Adaptation**: Unsupervised Domain Adaptation (UDA) is training a statistical model on labelled data to a **target domain data** from a **source domain** more efficiently, having access to only unlabeled data in the target domain.

- In principle, UDA mainly focuses on the **global distribution** alignment between domains while not including the local distribution properties.

- The goal is to utilize characteristics from a categorized source area and apply them to an **uncategorized target area** that has a comparable but distinct data distribution.

Related Works

- **Indian Road Scenes**: One of the key challenges in the semantic segmentation of Indian road scenes is the variability in the appearance of objects and features.

- Indian road scenes often contain a large number of pedestrians and other non-vehicular objects, which can further complicate the task of semantic segmentation.

- **A**dvanced **D**river **A**ssistance **S**ystems (**ADAS**) for Indian roads use cameras and other sensors to perceive the environment and make decisions about how to control the vehicle.

Proposed Solution

We test various SOTA architectures for semantic segmentation, including:

1. *CBST*
2. *BAPA*
3. *ProDA*
4. *DAFormer (best performance using UDA*)*

We draw the inferences on Indian road scene images to calculate the **mIoU** scores (**M**ean **I**ntersection **O**ver **U**nion) for all models and compare them against one another for performance.

DAFormer UDA Architecture

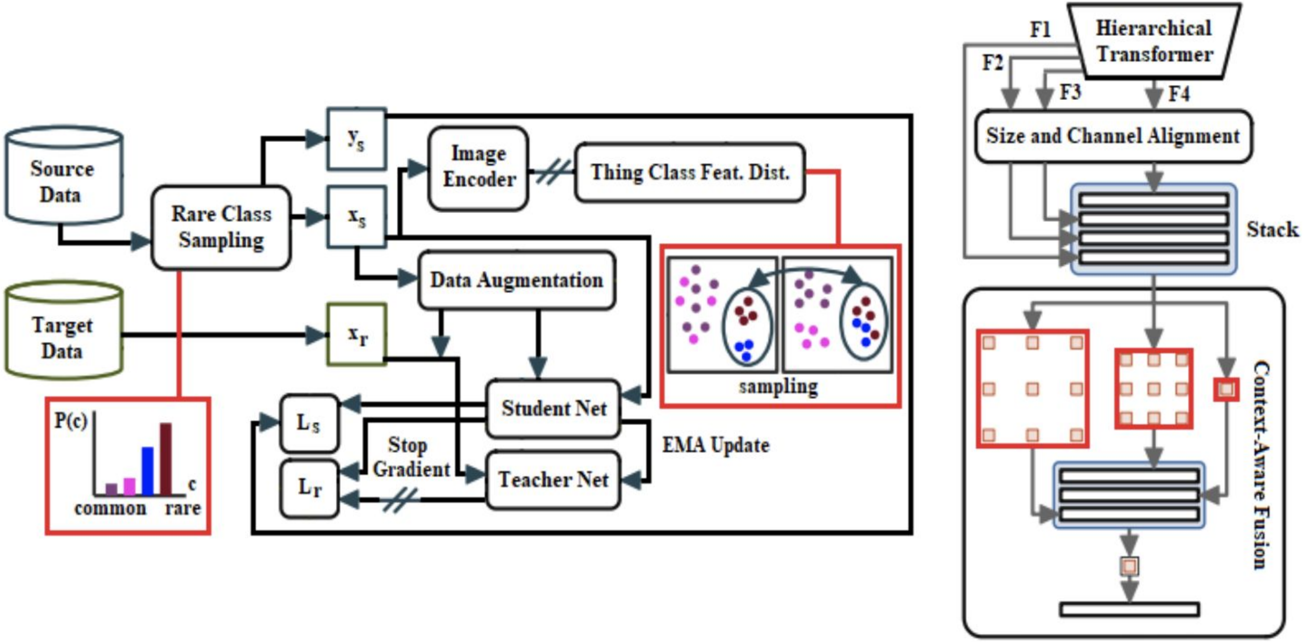


Fig. 1. Overview of the UDA framework with Rare Class Sampling, Thing-Class Feature Distance for the DAFormer model.

Benchmark Datasets

- **Cityscapes**
- Cityscapes is a comprehensive database that concentrates on comprehending urban street scenes semantically.

- Contains **30** different classes, divided into **8** categories (such as humans, vehicles, constructions, objects, nature, sky, and void); includes both instance-wise and dense pixel annotations.

- Dataset encompasses ~**5000** images with fine annotations and **20,000** with coarse annotations, captured in **50** cities over a period of several months only during daylight hours and good weather conditions.

Benchmark Datasets

- **GTA 5**: The GTA 5 dataset comprises **24,966 synthetic images** with pixel-level semantic labelling, created through the open-world video game Grand Theft Auto 5 featuring a car's view of American-style virtual cities.

- **19** semantic categories encompassing an extensive range of road scenes, from urban to rural, and provides comprehensive annotations for objects such as buildings, roads, vehicles, and pedestrians.

- **SYNTHIA**: The SYNTHIA dataset includes more than **200,000** high-definition images from video streams, as well as **20,000** images from separate snapshots.

- The scenes in this dataset feature a European-style town, modern city, highway, green areas, cars, pedestrians, and cyclists.

Benchmark Datasets

- **WIRIN National Dataset for Indian Roads**
- The National Dataset for Indian Roads is a dataset created for R&D in autonomous systems— specifically for Indian road scene analysis, in partnership by **IISc** and **Wipro Research** under the WIRIN initiative.

- Created to address the lack of publicly available datasets for Indian road scenes, having unique characteristics of such as crowded roads, diverse traffic, and a wide range of vehicle types.

- Includes **1,000** images captured from various locations in India with a resolution of **1920*1080 pixels**, annotated with **29** classes, including roads, buildings, vehicles, pedestrians, and traffic signs.

Benchmark Datasets

- **WIRIN National Dataset for Indian Roads**

  Number of classes in the given dataset: **29**

  Number of classes considered for comparison: **19**

  Number of classes rejected due to low sample size: **10** (marked in red)

1. road
2. sidewalk
3. building
4. wall
5. fence
6. pole
7. traffic_light
8. traffic_sign
9. vegetation
10. terrain
11. sky
12. person
13. car
14. truck
15. bus
16. train
17. motorcycle
18. bicycle
19. rider
20. unknown
21. tunnel
22. autorickshaw
23. animal
24. rail_track
25. guard_rail
26. miscellaneous_vehicles
27. pillar
28. bridge
29. divider

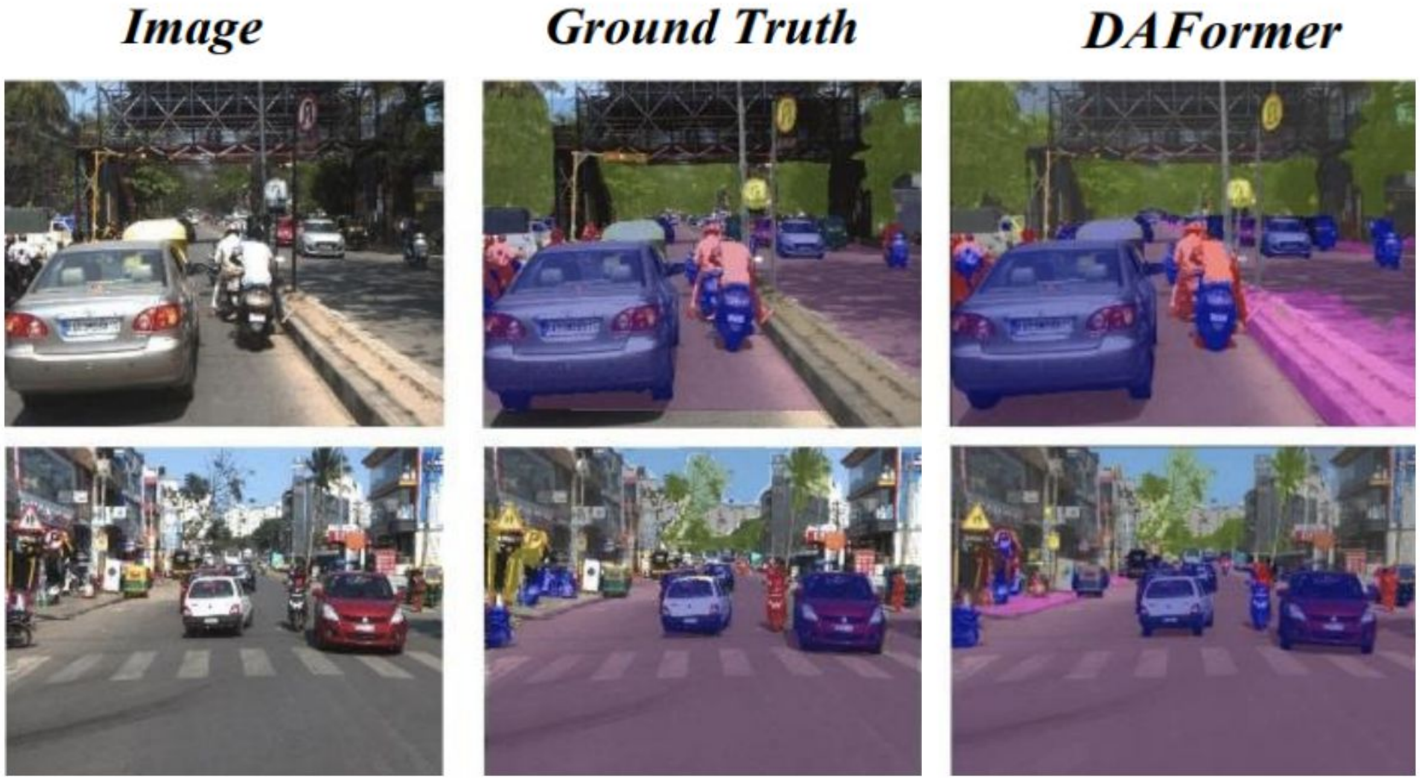
Visual Inference & Test Cases

Image *Ground Truth* *DAFormer*

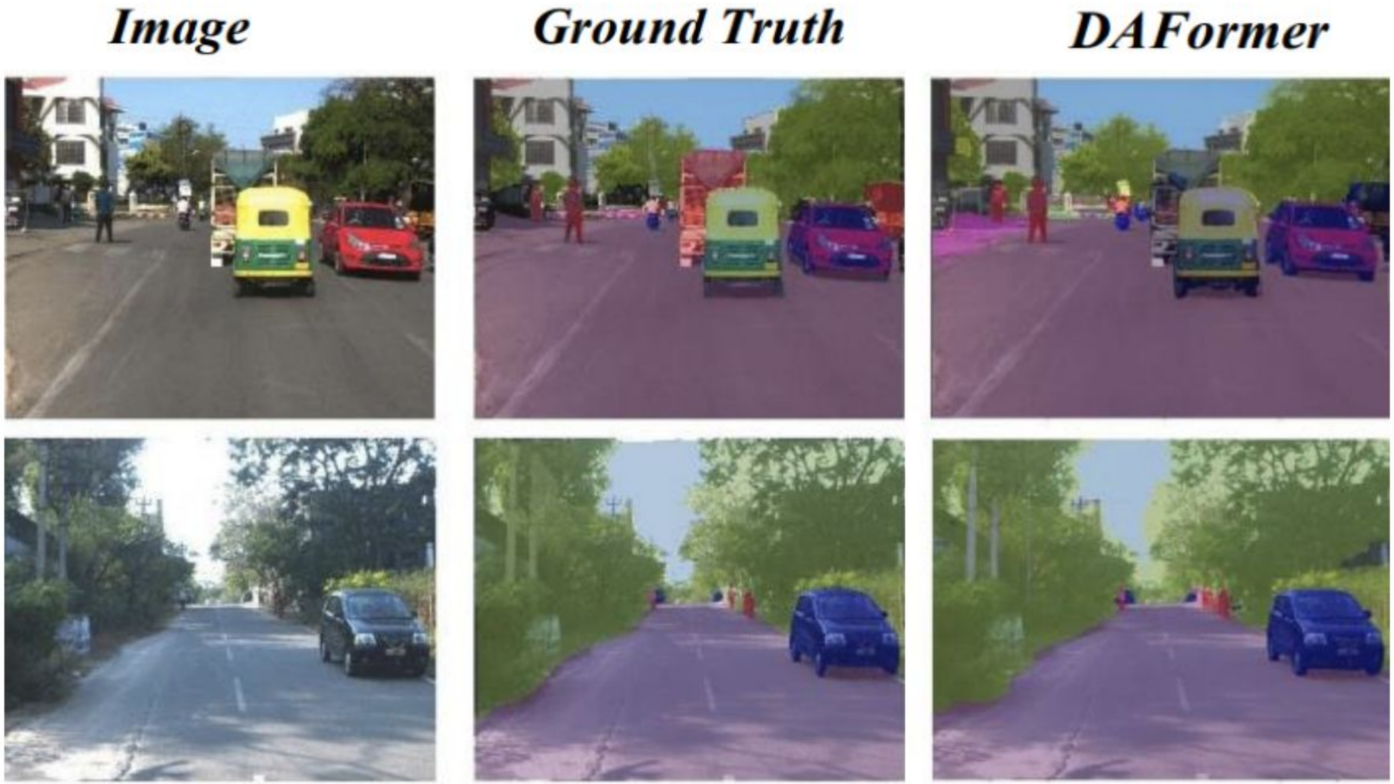
Visual Inference & Test Cases

Visual Inference & Test Cases

Visual Inference & Test Cases



Visual Inference & Test Cases



Performance Evaluation Summary

- Performance measurement metric used: **I**ntersection **O**ver **U**nion (**IoU**), and **M**ean **I**ntersection **O**ver **U**nion (**mIoU**)

- *But what are IoU and mIoU scores?*

- Intersection Over Union (IoU) is a number that quantifies the degree of overlap between two boxes. In the case of object detection and segmentation, IoU evaluates the overlap of the Ground Truth and Prediction region.

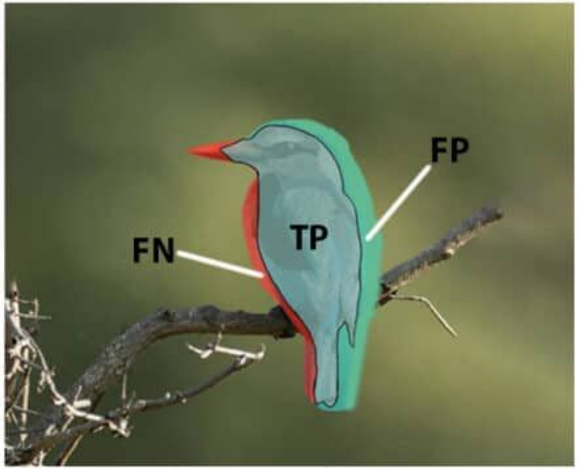
- The mean intersection over union (mIoU) score is the average of the IoU scores for a set of predicted and ground truth regions.
- It provides an overall measure of how well the predicted regions align with the ground truths by considering the average IoU score across all pairs of regions.

Performance Evaluation Summary

- In simpler terms…

Ground Truth Mask

Predicted Mask



$$IoU = \frac{TP}{(TP + FP + FN)}$$

where,
TP = True Positives; FP = False Positives
TN = True Negatives; FN = False Negatives

Performance Evaluation Summary: GTA→Cityscapes

Table 1. GTA5 TO CITYSCAPES

Classes	Models						
	CBST [22]	DACS [23]	CorDA [24]	BAPA [25]	ProDA [26]	DA-Former [20]	HRDA [27]
Road	91.8	89.9	94.7	94.4	87.8	95.7	96.4
Sidewalk	53.5	39.7	63.1	61	56	70.2	74.4
Building	80.5	87.9	87.6	88	79.7	89.4	91
Wall	32.7	30.7	30.7	26.8	46.3	53.5	61.6
Fence	21	39.5	40.6	39.9	44.8	48.1	51.5
Pole	34	38.5	40.2	38.3	45.6	49.6	57.1
Traffic Light	28.9	46.4	47.8	46.1	53.5	55.8	63.9
Sign	20.4	52.8	51.6	55.3	53.5	59.4	69.3
Vegetation	83.9	88	87.6	87.8	88.6	89.9	91.3
Terrain	34.2	44	47	46.1	45.2	47.9	48.4
Sky	80.9	88.8	89.7	89.4	82.1	92.5	94.2
Person	53.1	67.2	66.7	68.8	70.7	72.2	79
Rider	24	35.8	35.9	40	39.2	44.7	52.9
Car	82.7	84.5	90.2	90.2	88.8	92.3	93.9
Truck	30.3	45.7	48.9	60.4	45.5	74.5	84.1
Bus	35.9	50.2	57.5	59	59.4	78.2	85.7
Train	16	0	0	0	1	65.1	75.9
Motorbike	25.9	27.3	39.8	45.1	48.9	55.9	63.9
Bike	42.8	34	56	54.2	56.4	61.8	67.5
mIoU	**91.8**	**89.9**	**94.7**	**94.4**	**87.8**	**95.7**	**96.4**

Performance Evaluation Summary: SYNTHIA→Cityscapes

Table 2. SYNTHIA TO CITYSCAPES

Classes	Models						
	CBST [22]	DACS [23]	CorDA [24]	BAPA [25]	ProDA [26]	DA-Former [20]	HRDA [27]
Road	68	80.6	91.7	93.3	87.8	84.5	85.2
Sidewalk	29.9	25.1	53.8	61.6	45.7	40.7	47.7
Building	76.3	81.9	83.9	85.3	84.6	88.4	88.8
Wall	10.8	21.5	22.4	19.6	37.1	41.5	49.5
Fence	1.4	2.9	0.8	5.1	0.6	6.5	4.8
Pole	33.9	37.2	34.9	37.8	44	50	57.2
Traffic Light	22.8	22.7	30.5	36.6	54.6	55	65.7
Sign	29.5	24	42.8	42.8	37	54.6	60.9
Vegetation	77.6	83.7	86.6	84.9	88.1	86	85.3
Terrain	-	-	-	-	-	-	-
Sky	78.3	90.8	88.2	90.4	84.4	89.8	92.9
Person	60.6	67.6	66	69.7	74.2	73.2	79.4
Rider	28.3	38.3	34.1	41.8	24.3	48.2	52.8
Car	81.6	82.9	86.6	85.6	88.2	87.2	89
Truck	-	-	-	-	-	-	-
Bus	23.5	38.9	51.3	38.4	51.1	53.2	64.7
Train	-	-	-	-	-	-	-
Motorbike	18.8	28.5	29.4	32.6	40.5	53.9	63.9
Bike	39.8	47.6	50.5	53.9	45.6	61.7	64.9
mIoU	**68**	**80.6**	**91.7**	**93.3**	**87.8**	**84.5**	**85.2**

Performance Evaluation Summary: WIRIN Dataset

Table 3. NATIONAL DATASET FOR INDIAN ROADS

Classes	Models			
	CBST [22]	BAPA [23]	ProDA [26]	DAFormer [20]
Road	79.3	84.6	82.6	90.9
Sidewalk	45.4	54.2	52	66.9
Building	69.2	79.2	74.2	84.3
Wall	27.9	23.8	43.9	51.3
Fence	17.7	36.1	43.4	45.7
Pole	28.1	34	42.8	47.6
Traffic Light	26.6	42.9	47.5	53.2
Sign	17.4	49.7	49.5	57.1
Vegetation	73.5	77.4	82.3	85.9
Terrain	30	41.2	42	45.3
Sky	67.5	78.6	76.3	87.6
Person	42.1	62.3	65.7	69.1
Rider	20.4	35.6	36.5	42.8
Car	72.9	80.8	82.2	87.8
Truck	27.1	51.9	42.3	70.7
Bus	31.5	52.1	55.4	74.4
Train	13.4	0	0.9	61.8
Motorbike	22.8	41	45.7	53.4
Bike	38.3	48.5	52.4	59
mIoU	**78**	**84.6**	**81.6**	**90.7**

Performance Breakdown by Class: Road

Class/Model	Road		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	91.8	68	**79.3**
BAPA	94.4	93.3	**84.6**
ProDA	87.8	87.8	**82.6**
DAFormer	95.7	84.5	**90.9**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Sidewalk

Class/Model	Sidewalk		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	53.5	29.9	**45.4**
BAPA	61	61.6	**54.2**
ProDA	56	45.7	**52**
DAFormer	70.2	40.7	**66.9**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Building

Class/Model	Building		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	80.5	76.3	**69.2**
BAPA	88	85.3	**79.2**
ProDA	79.7	84.6	**74.2**
DAFormer	89.4	88.4	**84.3**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Wall

Class/Model	Wall		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	32.7	10.8	**27.9**
BAPA	26.8	19.6	**23.8**
ProDA	46.3	37.1	**43.9**
DAFormer	53.5	41.5	**51.3**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Fence

Class/Model	Fence		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	21	1.4	**17.7**
BAPA	39.9	5.1	**36.1**
ProDA	44.8	0.6	**43.4**
DAFormer	48.1	6.5	**45.7**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Pole

Class/Model	Pole		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	34	33.9	**28.1**
BAPA	38.3	37.8	**34**
ProDA	45.6	44	**42.8**
DAFormer	49.6	50	**47.6**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Traffic Lights

Class/Model	Traffic Lights		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	28.9	22.8	**26.6**
BAPA	46.1	36.6	**42.9**
ProDA	53.5	54.6	**47.5**
DAFormer	55.8	55	**53.2**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Sign

Class/Model	Sign		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	20.4	29.5	**17.4**
BAPA	55.3	42.8	**49.7**
ProDA	53.5	37	**49.5**
DAFormer	59.4	54.6	**57.1**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Vegetation

Class/Model	Vegetation		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	83.9	77.6	**73.5**
BAPA	87.8	84.9	**77.4**
ProDA	88.6	88.1	**82.3**
DAFormer	89.9	86	**85.9**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Terrain

Class/Model	Terrain		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	34.2	NA	**30**
BAPA	46.1	NA	**41.2**
ProDA	45.2	NA	**42**
DAFormer	47.9	NA	**45.3**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Sky

Class/Model	Sky		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	80.9	78.3	**67.5**
BAPA	89.4	90.4	**78.6**
ProDA	82.1	84.4	**76.3**
DAFormer	92.5	89.8	**87.6**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Person

Class/Model	Person		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	53.1	60.6	**42.1**
BAPA	68.8	69.7	**62.3**
ProDA	70.7	74.2	**65.7**
DAFormer	72.2	73.2	**69.1**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Rider

Class/Model	Rider		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	24	28.3	**20.4**
BAPA	40	41.8	**35.6**
ProDA	39.2	24.3	**36.5**
DAFormer	44.7	48.2	**42.8**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Car

Class/Model	Car		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	82.7	81.6	**72.9**
BAPA	90.2	85.6	**80.8**
ProDA	88.8	88.2	**82.2**
DAFormer	92.3	87.2	**87.8**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Truck

Class/Model	Truck		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	30.3	NA	**27.1**
BAPA	60.4	NA	**51.9**
ProDA	45.5	NA	**42.3**
DAFormer	74.5	NA	**70.7**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Bus

Class/Model	Bus		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	35.9	23.5	**31.5**
BAPA	59	38.4	**52.1**
ProDA	59.4	51.1	**55.4**
DAFormer	78.2	53.2	**74.4**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Train

Class/Model	Train		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	16	NA	**13.4**
BAPA	0	NA	**0**
ProDA	1	NA	**0.9**
DAFormer	65.1	NA	**61.8**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Motorbike

Class/Model	Motorbike		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	25.9	18.8	**22.8**
BAPA	45.1	32.6	**41**
ProDA	48.9	40.5	**45.7**
DAFormer	55.9	53.9	**53.4**

Intersection over Union (IoU) scores

Performance Breakdown by Class: Bike

Class/Model	Bike		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	42.8	39.8	**38.3**
BAPA	54.2	53.9	**48.5**
ProDA	56.4	45.6	**52.4**
DAFormer	61.8	61.7	**59**

Intersection over Union (IoU) scores

Performance Evaluation Parameter: <u>Mean Intersection Over Union (mIoU)</u>

Class/Model	mIoU		
	GTA5 to Cityscapes	SYNTHIA to Cityscapes	**WIRIN**
CBST	91.8	68	**78**
BAPA	94.4	93.3	**84.6**
ProDA	87.8	87.8	**81.6**
DAFormer	95.7	84.5	**90.7**

Conclusion

- Unsupervised Domain Adaptation has proven to be a promising solution by fine-tuning pre-trained models on the target domain using limited labeled data.

- This approach has shown positive results for different types of Indian road scenes, with the ability to accurately segment road surfaces and objects like vehicles, pedestrians and buildings.

- UDA also increases the generalization of the models to new scenes, which is crucial for practical applications.

- However, there are still some challenges to be overcome, such as the models' incapacity to fully capture variations like weather conditions, etc.

References

- Hoyer, L., Dai, D., Van Gool, L.: DAFormer: Improving network architectures and training strategies for domain-adaptive semantic segmentation. In: CVPR (2022).
- Tranheden, W., Olsson, V., Pinto, J., Svensson, L.: DACS: Domain Adaptation via Crossdomain Mixed Sampling. In: WACV. pp. 1379– 1389 (2021).
- Zou, Y., Yu, Z., Kumar, B., Wang, J.: Unsupervised domain adaptation for semantic segmentation via class-balanced self-training. In: ECCV. pp. 289–305 (2018).
- Tranheden, W., Olsson, V., Pinto, J., Svensson, L.: DACS: Domain Adaptation via Crossdomain Mixed Sampling. In: WACV. pp. 1379–1389 (2021).
- Wang, Q., Dai, D., Hoyer, L., Fink, O., Van Gool, L.: Domain adaptive semantic segmentation with self-supervised depth estimation. In: ICCV. pp. 8515–8525 (2021).
- Liu, Y., Deng, J., Gao, X., Li, W., Duan, L.: Bapa-net: Boundary adaptation and prototype alignment for cross-domain semantic segmentation. In: ICCV. pp. 8801–8811 (2021).
- Zhang, P., Zhang, B., Zhang, T., Chen, D., Wang, Y., Wen, F.: Prototypical pseudo label denoising and target structure learning for domain adaptive semantic segmentation. CVPR. pp. 1214–1224 (2021).
- Hoyer, L., Dai, D., & Van Gool, L. (2022). HRDA: Context-Aware High-Resolution Domain-Adaptive Semantic Segmentation. arXiv preprint arXiv:2204.13132.

References

- Dewangan, Deepak Kumar, and Satya Prakash Sahu. "Road detection using semantic segmentation-based convolutional neural network for intelligent vehicle system." In Data Engineering and Communication Technology: Proceedings of ICDECT 2020, pp. 629-637. Springer Singapore, 2021.
- Kalluri, Tarun, Girish Varma, Manmohan Chandraker, and C. V. Jawahar. "Universal semi-supervised semantic segmentation." In Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 5259-5270. 2019.
- Xiong, Zhuoran, Marihan Amein, Olivier Therrien, Warren J. Gross, and Brett H. Meyer. "FMAS: Fast Multi-Objective SuperNet Architecture Search for Semantic Segmentation." arXiv preprint arXiv:2303.16322 (2023).
- Shi, Jianguo, and Qingyun Xu. "An Image Semantic Segmentation Method with Improved Network Structure." In 2023 IEEE 6th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), vol. 6, pp. 1700-1705. IEEE, 2023.
- Fan, Zhiyong, Kailai Liu, Jianmin Hou, Fei Yan, and Qiang Zang. "JAUNet: A U-Shape Network with Jump Attention for Semantic Segmentation of Road Scenes." Applied Sciences 13, no. 3 (2023): 1493.
- Chen, Yuqi, Xiangbin Zhu, Yonggang Li, Yuanwang Wei, and Lihua Ye. "Enhanced semantic feature pyramid network for small object detection." Signal Processing: Image Communication (2023): 116919.

References

- Chen, Runnan, Youquan Liu, Lingdong Kong, Xinge Zhu, Yuexin Ma, Yikang Li, Yuenan Hou, Yu Qiao, and Wenping Wang. "CLIP2Scene: Towards Label-efficient 3D Scene Understanding by CLIP." arXiv preprint arXiv:2301.04926 (2023).
- Baheti, B., Gajre, S., & Talbar, S. (2019, October). Semantic scene understanding in unstructured environment with deep convolutional neural network. In TENCON 2019-2019 IEEE Region 10 Conference (TENCON) (pp. 790-795). IEEE.
- Islam, Ashraful, Benjamin Lundell, Harpreet Sawhney, Sudipta N. Sinha, Peter Morales, and Richard J. Radke. "Self-supervised Learning with Local Contrastive Loss for Detection and Semantic Segmentation." In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pp. 5624-5633. 2023.
- Garg, Prachi, Rohit Saluja, Vineeth N. Balasubramanian, Chetan Arora, Anbumani Subramanian, and C. V. Jawahar. "Multi-domain incremental learning for semantic segmentation." In Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, pp. 761-771. 2022.
- Tiwari, Twinkle, and Mukesh Saraswat. "A new modified-unet deep learning model for semantic segmentation." Multimedia Tools and Applications 82, no. 3 (2023): 3605-3625.
- Hong, Y., Pan, H., Sun, W., & Jia, Y. (2021). Deep dual-resolution networks for real-time and accurate semantic segmentation of road scenes. arXiv preprint arXiv:2101.06085.

References

- M. Kumar, A. Tewari, M. S. Gaur, and D. Parashar, "Semantic Segmentation of Indian Road Scenes," in 2018 5th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India, 2018, pp. 307-312. doi: 10.1109/SPIN.2018.8474041.
- V. Kulkarni and M. M. Kawade, "Semantic Segmentation of Indian Road Scenes using Fully Convolutional Neural Networks," in 2020 IEEE 6th International Conference for 12 Convergence in Technology (I2CT), Pune, India, 2020, pp. 1-6. doi: 10.1109/I2CT48456.2020.9161021.
- Chen, Y., Li, W., & Van Gool, L. (2018). Road: Reality oriented adaptation for semantic segmentation of urban scenes. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 7892-7901).
- R. K. Gouda and S. K. Lenka, "A Survey on Indian Road Scene Semantic Segmentation," in 2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT), Kannur, India, 2019, pp. 2052-2056. doi: 10.1109/ICICICT47697.2019.9073619.
- Shashaani, Shahrzad, Mohammad Teshnehlab, Amirreza Khodadadian, Maryam Parvizi, Thomas Wick, and Nima Noii. "Using layer-wise training for Road Semantic Segmentation in Autonomous Cars." IEEE Access (2023).

References

- Xie, E., Wang, W., Yu, Z., Anandkumar, A., Alvarez, J. M., & Luo, P. (2021). SegFormer: Simple and efficient design for semantic segmentation with transformers. Advances in Neural Information Processing Systems, 34, 12077-12090.
- Hoyer, L., Dai, D., Van Gool, L.: DAFormer: Improving network architectures and training strategies for domain-adaptive semantic segmentation. In: CVPR (2022).
- Tranheden, W., Olsson, V., Pinto, J., Svensson, L.: DACS: Domain Adaptation via Crossdomain Mixed Sampling. In: WACV. pp. 1379– 1389 (2021).
- Zou, Y., Yu, Z., Kumar, B., Wang, J.: Unsupervised domain adaptation for semantic segmentation via class-balanced self-training. In: ECCV. pp. 289–305 (2018).
- Tranheden, W., Olsson, V., Pinto, J., Svensson, L.: DACS: Domain Adaptation via Crossdomain Mixed Sampling. In: WACV. pp. 1379–1389 (2021).
- Wang, Q., Dai, D., Hoyer, L., Fink, O., Van Gool, L.: Domain adaptive semantic segmentation with self-supervised depth estimation. In: ICCV. pp. 8515–8525 (2021).
- Liu, Y., Deng, J., Gao, X., Li, W., Duan, L.: Bapa-net: Boundary adaptation and prototype alignment for cross-domain semantic segmentation. In: ICCV. pp. 8801–8811 (2021).

References

- Zhang, P., Zhang, B., Zhang, T., Chen, D., Wang, Y., Wen, F.: Prototypical pseudo label denoising and target structure learning for domain adaptive semantic segmentation. In: CVPR. pp. 12414–12424 (2021).
- Hoyer, L., Dai, D., & Van Gool, L. (2022). HRDA: Context-Aware High-Resolution Domain-Adaptive Semantic Segmentation. arXiv preprint arXiv:2204.13132.
- Wu, Zhiyuan, Yu Jiang, Chupeng Cui, Zongmin Yang, Xinhui Xue, and Hong Qi. "Spirit distillation: Precise real-time semantic segmentation of road scenes with insufficient data." arXiv preprint arXiv:2103.13733 (2021).
- Deng, Yifan, Shaoqing Mo, Haiyun Gan, and Jiangjiang Wu. "Research on Traffic Scene Recognition Algorithm Combining Object Detection and Semantic Segmentation." Academic Journal of Computing & Information Science 6, no. 3 (2023): 75-83.
- Butilă, Eugen Valentin, and Răzvan Gabriel Boboc. 2022. "Urban Traffic Monitoring and Analysis Using Unmanned Aerial Vehicles (UAVs): A Systematic Literature Review" Remote Sensing 14, no. 3: 620. https://doi.org/10.3390/rs14030620.