Semantic Segmentation With Multi Scale Spatial Attention For Self Driving Cars

Abhinav Sagar*
Vellore Institute of Technology
Vellore, Tamil Nadu, India
abhinavsagar4@gmail.com

RajKumar Soundrapandiyan †
Vellore Institute of Technology
Vellore, Tamil Nadu, India
rajkumar.s@vit.ac.in

Abstract

In this paper, we present a novel neural network using multi scale feature fusion at various scales for accurate and efficient semantic image segmentation. We have used dilated convolutional layers in downsampling part, transposed convolutional layers in the upsampling part and used concat layers to merge them. We used skip connections in between alternate blocks which are comprised of convolutional and max pooling layers. We present an in depth theoretical analysis of our network with training and optimization details. We evaluated our network on the Camvid dataset using mean accuracy per class and Intersection Over Union (IOU) as the evaluation metrics on the test set. Our model outperforms previous state of the art networks on semantic segmentation achieving mean IOU value of 74.12 while running at >100 FPS.

1 Introduction

Convolutional neural networks has seen a lot of success in tasks involving classification, detection and segmentation. These include bounding box object detection, pose estimation, keypoint prediction and image segmentation. CNN-based neural networks advances, such as dropout (Srivastava et al., 2014) and batch normalization (Ioffe and Szegedy, 2015) have helped avoid some of the common challenges faced earlier like the curse of dimensionality and vanishing gradient problem while training neural networks. Convolutional networks are now leading many computer vision tasks, including image classification (Deng et al., 2009), object detection (Girshick et al., 2014), (Zhu et al., 2015) and (Liu and He, 2015) and semantic image segmentation (Chen et al., 2014), (Li et al., 2014) and (Zhao et al., 2017). Semantic segmentation is also known as scene parsing, which aims to classify each and every pixel present in the image. It is one of the most challenging and important tasks in computer vision. The famous fully convolutional network (FCN) (Long et al., 2015) for semantic segmentation is based on VGG-Net (Simonyan and Zisserman, 2014), which is trained on the famous ImageNet dataset (Deng et al., 2009).

Segmentation task is different from classification task because it requires predicting a class for each and every pixel of the input image, instead of only discrete classes for the whole input images. In order to predict what is present in the image for each and every pixel, segmentation needs to find not only what is in the input image, but also where it is. It has a number of potential applications in the fields of autonomous driving, video surveillance, medical imaging etc. This is a challenging problem as there is often a tradeoff between accuracy and speed. Since the model eventually needs to be deployed in real world setting, hence both accuracy and speed should be high.

*Website of author - https://abhinavsagar.github.io/
†Website of author - https://sites.google.com/site/rajkumarsrajkumar/

Preprint. Under review.

2 Related Work

State-of-the-art methods on semantic segmentation have heavily relied on CNN models trained on large labeled datasets. Fully convolutional networks (FCN) trained pixels-to-pixels using skip connections that combines semantic information from a deep, coarse layer with appearance information from a shallow, fine layer to produce accurate and detailed segmentations. Convolution layers with a kernel size of 1×1 take the place of fully connected layers, followed by unpooling layers to recover the spatial resolution of the feature maps. The success of FCN is due to the great improvements in performance and because it showed that CNN can efficiently learn how to make dense class predictions for semantic segmentation. After FCN, recently proposed models are mainly designed by (1) bringing out novel decoder structure of the networks (Girshick et al., 2014) and (Badrinarayanan et al., 2017); (2) adopting more efficient basic classification models (Liu et al., 2015) and (Bittel et al., 2015); (3) adding integrating context knowledge with some independent modules (Zhu et al., 2015) and (Ronneberger et al., 2015). SegNet (Badrinarayanan et al., 2017) used an alternative decoder variant, in which an encoder decoder convolution path was proposed. Another deconvolution network was used in (Noh et al., 2015) with a similar decoder path as SegNet, but they adopted deconvolution modules to implement upsampling operations. (Ronneberger et al., 2015) added a 2×2 up-convolution layer, with a concatenation with corresponding pooling layer in U-Net. FCCN (Lin et al., 2016) could also be regarded as an alternative decoder structure.

(Chen et al., 2018) used atrous spatial pyramid pooling to embed contextual information at various scales which consist of parallel dilated convolutions with different dilation rates. (Zhao et al., 2017) used multi-scale contextual information by combining feature maps generated using different dilated convolutions and pooling operations. (Lin et al., 2017) proposed to fuse mid-level and high-level semantic features using an encoder decoder architecture. (Paszke et al., 2016) reduced the number of downsampling times to get an extremely tight fusion structure. (Zhao et al., 2018) uses multi-scale images as input and a cascade network to raise efficiency. (Li et al., 2019) uses Subnetwork Aggregation and Sub-stage Aggregation to achieve very high FPS and high accuracy using modified Xception bottleneck. (Yu et al., 2018a) uses spatial path to recover spatial information and to implement real-time calculation.

We summarize our main contributions as follows:

• We propose a new model architecture which used dilated convolutional layers in downsampling part and transposed convolutional layers in upsampling at multiple scales.

• We present the layer wise details, optimization and ablation study of our neural network.

• On evaluating our network on Camvid dataset using mean accuracy per class and IOU, our model outperforms previous state of the art model architectures while running at > 100 FPS.

3 Proposed Method

3.1 Dataset

The Cambridge-driving Labeled Video Database (CamVid) is a collection of videos with object class semantic labels, complete with metadata. The database provides ground truth labels that associate each pixel with one of 32 classes. The images are of size 360×480. A sample image from dataset is shown in Fig 1:

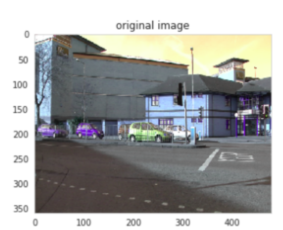


Figure 1: Ground truth image from dataset

The original images are taken as ground truth. For any algorithm, the metrics are always evaluated in comparison to the ground truth data. The ground truth information is provided in the dataset for the training and test set. For semantic segmentation problems, the ground truth includes the image, the classes of the objects in it and a segmentation mask for each and every object present in a particular image.

Since there is a lot of overlaps in between the labels, hence for the sake of convenience we have gone with 12 labels in this work. These images are shown in binary format for each label separately in Fig 2:

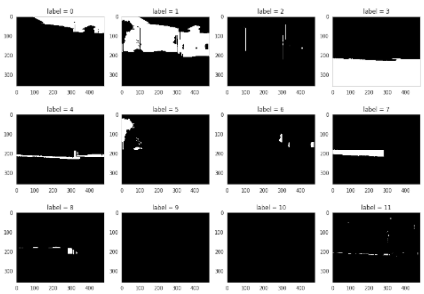


Figure 2: Images converted to binary class mask

The classes chosen from the dataset are Sky, Building, Pole, Road, Pavement, Tree, SignSymbol, Fence, Car, Pedestrian and Bicyclist.

3.2 Model Architecture

We resized the images to 224×224 pixels which was originally at 360×480 pixels. The reason is using VGG16 as the pretrained backbone requires input to be of shape 224×224 for training the model instead of training from scratch. We split the dataset into 2 parts with 85 percent images in the training set and 15 percent images in the test set. The loss function used is categorical cross entropy. We used dilated convolution in place of normal convolution layers in downsampling layers. We used transposed convolution in place of normal convolution layers in upsampling layers. We used four downsampling layers to reduce the feature maps and four upsampling layers to recover the features. We used concat operation in between the layers to merge the features at different scales.

For the convolutional layer we didn't use any padding, used 3×3 filter and use relu as the activation function. For the max pooling layer, we used 2×2 filters and strides of 2×2. We used VGG16 as the pre trained backbone for training the model. This makes the model learn low level features like edges from the pre trained weights. On top of it we have used two convolutional layers with relu as the activation function and strides of 7×7 and 1×1 respectively. In the upsampling path we used four transposed convolutions layers with 4×4 kernel size and strides of 4×4. The last layer is also a transposed convolution with 8×8 kernel size and 8×8 filter. Softmax is used as the activation function in the last layer to output discrete probabilities of whether an object is present in a particular pixel location or not. We used Adam as the optimizer. The batch size value of 4 was used which we found to be optimal to avoid overfitting. The details in regards to filter size, dilation, receptive field, feature maps and activation function used at every layer is shown in Table 1:

Table 1: Layer wise details

Layer	1	2	3	4	5	6
FilterSize	3×3	3×3	3×3	3×3	3×3	3×3
Dilation(Width, Height)	(1, 1)	(1, 2)	(2, 4)	(4, 8)	(8, 16)	(16, 32)
Receptive Field	3×3	5×7	9×15	17×31	33×63	65×127
Feature Maps	128	128	128	128	128	32
Non Linearity	ReLU	ReLU	ReLU	ReLU	ReLU	ReLU

The network architecture used in this work is shown in Fig 3:

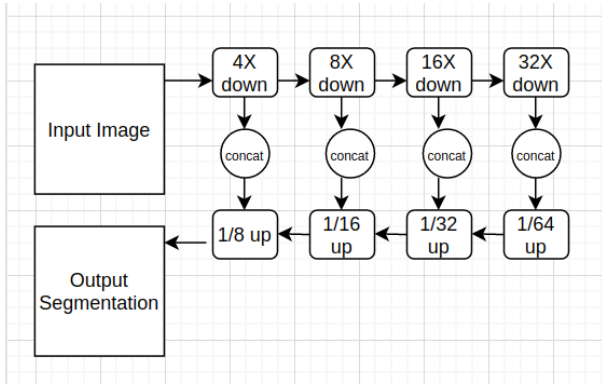


Figure 3: Our Neural network architecture

3.3 Optimization

Suppose given a local feature C, we feed it into a convolution layers to generate two new feature maps B and C respectively. After that we perform a matrix multiplication between the transpose of A and B, and apply a softmax layer to calculate the spatial attention map as shown in Equation 1:

$$s_{ji} = \frac{\exp\left(A_i \cdot B_j\right)}{\sum_{i=1}^{N} \exp\left(A_i \cdot B_j\right)} \tag{1}$$

We then perform a matrix multiplication between the transpose of X and A and reshape their results. Then we multiply the result by a scale parameter β and perform an element-wise sum operation with A to obtain the final output as shown in Equation 2:

$$E_j = \alpha \sum_{i=1}^{N} \left(s_{ji} D_i\right) + C_j \tag{2}$$

The Equation 2 shows that the resultant feature of each channel is a weighted sum of the features of all channels and models the semantic dependencies between feature maps at various scales. For a single backbone $\phi n(x)$, a stage process, the stage in the previous backbone network and sub-stage aggregation method can be formulated as shown in Equation 3:

$$x_n^i = \begin{cases} x_n^{i-1} + \phi_n^i\left(x_n^{i-1}\right) \\ \left[x_n^{i-1}, x_{n-1}^i\right] + \phi_n^i\left(\left[x_n^{i-1}, x_{n-1}^i\right]\right) \end{cases} \tag{3}$$

Here i refers to the index of the stage. The effect of the number of pooling layers on Intersection Over Union(IOU) is shown in Table 2. As can be noted, using more pooling layers increases IOU but it's effect is not consistent.

Table 2: Results on Camvid dataset with different numbers of pooling in each stage of the backbone, "×N" means the number of pooling.

Number of pooling	mIoU(%)
Pooling ×0	70.4
Pooling ×1	71.3
Pooling ×2	73.8
Pooling ×3	73.4
Pooling ×4	74.9
Pooling ×5	75.6

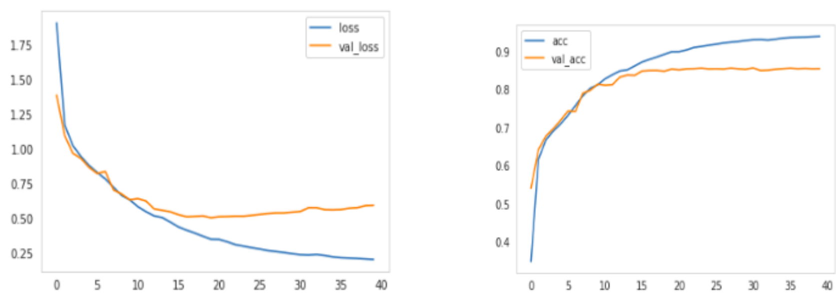
The effect of varying the number of branches and fusion methods used in model architecture on IOU is shown in Table 3. Using more number of branches and concat fusion instead of not using one increases the IOU.

Table 3: Results on Camvid dataset with with different number of branches and fusion methods.

Number of branches	Fusion methods	mIoU(%)
1	None	74.4
1	concat	75.8
2	None	75.7
2	concat	77.5

4 Experimental Results

In this section we present the results of our work and compare the results we achieved with previous state of the art. The model is trained for 40 epochs and reaches a training mean pixel accuracy of 93 percent and validation mean pixel accuracy of 88 percent. The loss and pixel wise accuracy (both training and test) are plotted as a function of epochs in Fig 4:



a) b)

Figure 4: a) Loss vs epochs b) Accuracy vs epochs

For evaluating the performance of our model architecture, we used two evaluation metrics:

1. Mean Accuracy per-class - This metric outputs the class wise prediction accuracy per pixel.

2. Mean IOU - It is a segmentation performance parameter that measures the overlap between two objects by calculating the ratio of intersection and union with ground truth masks. This metric is also known as Jaccard Index.

The class wise IOU values were calculated using Equation 4.

$$IoU = \frac{TP}{(TP + FP + FN)} \tag{4}$$

Where TP denotes true positive, FP denotes false positive, FN denotes false negative and IOU denotes Intersection over union value.

We next present the class wise IOU values for all the twelve classes present in Table 4.

Table 4: IOU values for all classes

Class	1	2	3	4	5	6	7	8	9	10	11	12
IOU	0.923	0.905	0.232	0.947	0.831	0.344	0.569	0.792	0.283	0.261	0.457	0.527

The effect of using multiple blocks, FLOPS and parameters on IOU is shown in Table 5. Here FLOPS and parameters are a measure of computation required by our model architecture.

Table 5: Detailed performance comparison of our proposed aggregation strategy. '×N' means that we replicate N backbones to implement feature aggregation

Model	FLOPs(G)	Params(M)	mIoU(%)
Backbone A	1.4	2.2	64.7
Backbone A ×2	2.3	4.5	65.3
Backbone A ×3	2.7	7.4	62.1
Backbone A ×4	2.9	10.6	57.8
Backbone B	0.8	1.4	59.5
Backbone B ×2	1.2	3.3	61.5
Backbone B ×3	1.4	4.7	56.4
Backbone B ×4	1.5	6.1	52.7

A comparative analysis on FPS and IOU achieved by previous state of the art model architectures vs ours is shown in Table 6.

Table 6: Accuracy and speed analysis on CamVid test dataset. Ours is 512×768 input and others are 768×1024 input.

Model	Frame(fps)	mIoU(%)
DPN (Yu et al., 2018b)	1.2	60.1
DeepLab (Chen et al., 2017)	4.9	61.6
ENet (Paszke et al., 2016)	-	51.3
ICNet (Zhao et al., 2018)	27.8	67.1
BiSeNet1 (Yu et al., 2018a)	-	65.6
BiSeNet2 (Yu et al., 2018a)	-	68.7
DFANet A (Li et al., 2019)	120	64.7
DFANet B (Li et al., 2019)	160	59.3
SwiftNet pyr (Orsic et al., 2019)	-	72.85
SwiftNet (Orsic et al., 2019)	-	73.86
Ours	124	74.12

The results comparing the predicted segmentations vs ground truth image from dataset is shown in Fig 5.

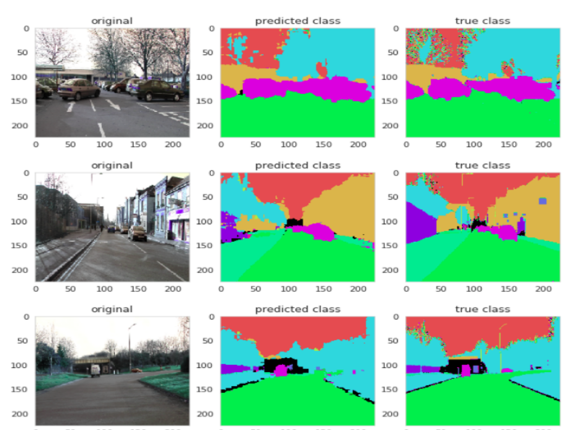


Figure 5: Results for predicted image - original image from dataset, predicted image from our network and ground truth image from dataset

5 Conclusions

In this paper, we proposed a semantic segmentation network using multi scale attention feature maps and validated its performance on Camvid semantic segmentation dataset. We used a downsampling and upsampling structure with dilated and transposed convolutional layers respectively with combinations between corresponding pooling and unpooling layers. This training class wise pixel accuracy achieved was 93 percent, validation class wise pixel accuracy was 88 percent and mean IOU value of 74.12 which is better than the previous state of the art on semantic segmentation while running at >100 FPS.

Acknowledgments

We would like to thank Nvidia for providing the GPUs.

References

A. F. Agarap. Deep learning using rectified linear units (relu). *arXiv preprint arXiv:1803.08375*, 2018.

V. Badrinarayanan, A. Kendall, and R. Cipolla. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. *IEEE transactions on pattern analysis and machine intelligence*, 39(12):2481–2495, 2017.

S. Bittel, V. Kaiser, M. Teichmann, and M. Thoma. Pixel-wise segmentation of street with neural networks. *arXiv preprint arXiv:1511.00513*, 2015.

L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille. Semantic image segmentation with deep convolutional nets and fully connected crfs. *arXiv preprint arXiv:1412.7062*, 2014.

L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, and A. L. Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *IEEE transactions on pattern analysis and machine intelligence*, 40(4):834–848, 2017.

L.-C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In *Proceedings of the European conference on computer vision (ECCV)*, pages 801–818, 2018.

J. Dai, K. He, Y. Li, S. Ren, and J. Sun. Instance-sensitive fully convolutional networks. In *European Conference on Computer Vision*, pages 534–549. Springer, 2016.

J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pages 248–255. Ieee, 2009.

M. Everingham, L. Van Gool, C. K. Williams, J. Winn, and A. Zisserman. The pascal visual object classes (voc) challenge. *International journal of computer vision*, 88(2):303–338, 2010.

R. Gadde, V. Jampani, and P. V. Gehler. Semantic video cnns through representation warping. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 4453–4462, 2017.

R. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 580–587, 2014.

S. Ioffe and C. Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*, 2015.

S. Jégou, M. Drozdzal, D. Vazquez, A. Romero, and Y. Bengio. The one hundred layers tiramisu: Fully convolutional densenets for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, pages 11–19, 2017.

D. P. Kingma and J. Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

H. Li, R. Zhao, and X. Wang. Highly efficient forward and backward propagation of convolutional neural networks for pixelwise classification. *arXiv preprint arXiv:1412.4526*, 2014.

H. Li, P. Xiong, H. Fan, and J. Sun. Dfanet: Deep feature aggregation for real-time semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 9522–9531, 2019.

G. Lin, C. Shen, A. Van Den Hengel, and I. Reid. Efficient piecewise training of deep structured models for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3194–3203, 2016.

G. Lin, A. Milan, C. Shen, and I. Reid. Refinenet: Multi-path refinement networks for high-resolution semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1925–1934, 2017.

B. Liu and X. He. Multiclass semantic video segmentation with object-level active inference. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4286–4294, 2015.

Z. Liu, X. Li, P. Luo, C.-C. Loy, and X. Tang. Semantic image segmentation via deep parsing network. In *Proceedings of the IEEE international conference on computer vision*, pages 1377–1385, 2015.

J. Long, E. Shelhamer, and T. Darrell. Fully convolutional networks for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 3431–3440, 2015.

H. Noh, S. Hong, and B. Han. Learning deconvolution network for semantic segmentation. In *Proceedings of the IEEE international conference on computer vision*, pages 1520–1528, 2015.

M. Orsic, I. Kreso, P. Bevandic, and S. Segvic. In defense of pre-trained imagenet architectures for real-time semantic segmentation of road-driving images. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 12607–12616, 2019.

A. Paszke, A. Chaurasia, S. Kim, and E. Culurciello. Enet: A deep neural network architecture for real-time semantic segmentation. *arXiv preprint arXiv:1606.02147*, 2016.

C. Peng, X. Zhang, G. Yu, G. Luo, and J. Sun. Large kernel matters–improve semantic segmentation by global convolutional network. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4353–4361, 2017.

S. Ren, K. He, R. Girshick, and J. Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems*, pages 91–99, 2015.

E. Romera, J. M. Alvarez, L. M. Bergasa, and R. Arroyo. Erfnet: Efficient residual factorized convnet for real-time semantic segmentation. *IEEE Transactions on Intelligent Transportation Systems*, 19 (1):263–272, 2017.

O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

A. Sagar. Learning to detect 3d objects from point clouds in real time. *arXiv preprint arXiv:2006.01250*, 2020.

K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov. Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, 15(1): 1929–1958, 2014.

C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1–9, 2015.

P. Wang, P. Chen, Y. Yuan, D. Liu, Z. Huang, X. Hou, and G. Cottrell. Understanding convolution for semantic segmentation. In *2018 IEEE winter conference on applications of computer vision (WACV)*, pages 1451–1460. IEEE, 2018.

C. Yu, J. Wang, C. Peng, C. Gao, G. Yu, and N. Sang. Bisenet: Bilateral segmentation network for real-time semantic segmentation. In *Proceedings of the European conference on computer vision (ECCV)*, pages 325–341, 2018a.

C. Yu, J. Wang, C. Peng, C. Gao, G. Yu, and N. Sang. Learning a discriminative feature network for semantic segmentation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1857–1866, 2018b.

F. Yu and V. Koltun. Multi-scale context aggregation by dilated convolutions. *arXiv preprint arXiv:1511.07122*, 2015.

H. Zhang, K. Dana, J. Shi, Z. Zhang, X. Wang, A. Tyagi, and A. Agrawal. Context encoding for semantic segmentation. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 7151–7160, 2018.

H. Zhao, J. Shi, X. Qi, X. Wang, and J. Jia. Pyramid scene parsing network. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2881–2890, 2017.

H. Zhao, X. Qi, X. Shen, J. Shi, and J. Jia. Icnet for real-time semantic segmentation on high-resolution images. In *Proceedings of the European Conference on Computer Vision (ECCV)*, pages 405–420, 2018.

Y. Zhu, R. Urtasun, R. Salakhutdinov, and S. Fidler. segdeepm: Exploiting segmentation and context in deep neural networks for object detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4703–4711, 2015.