Evolution of Image Segmentation using Deep Convolutional Neural Network: A Survey

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Abstract

From the autonomous car driving to medical diagnosis, the requirement of the task of image segmentation is everywhere. Segmentation of an image is one of the indispensable tasks in computer vision. This task is comparatively complicated than other vision tasks as it needs low level spatial information. Basically, image segmentation can be of two types: semantic segmentation and instance segmentation. The combined version of these two basic tasks is known as panoptic segmentation. In the recent era, the success of deep convolutional neural network (CNN) has influenced the field of segmentation greatly and gave us various successful models till date. In this survey, we are going to take a glance on the evolution of both semantic and instance segmentation work based on CNN. We have also specified architectural details of some state-of-the-art models and discuss their comparative training details to present a lucid understanding of hyper-parameter tuning of those models. We have also drawn a comparison among the performance of those models on different datasets.

Keywords: Convolutional Neural Network, Deep Learning, Semantic Segmentation, Instance Segmentation, Panoptic Segmentation, Survey

1. Introduction

We are living in the era of artificial intelligence (AI) and the advancement of deep learning is fueling AI to spread over rapidly [1], [2], [3]. Among dif-

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different deep learning models, convolutional neural network (CNN) has shown outstanding performance in different high level computer vision task such as image classification [4, 5, 6, 7, 8, 9, 10, 11, 12, 13], object detection [14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26] etc. Though the advent and success of AlexNet [4] turned the field of computer vision towards CNN from traditional machine learning algorithms. But the concept of CNN was not a new one. It started from the discovery of Hubel and Wiesel [27] which explained that there are simple and complex neurons in the primary visual cortex and the visual processing always starts with simple structures such as oriented edges. Inspired by this idea, David Marr gave us the next insight that vision is hierarchical [28]. Kunihiko Fukushima was deeply inspired by the work of Hubel and Wiesel and built a multi-layered neural network called Neocognitron [29] using simple and complex neurons. It was able to recognize patterns in images and was spatial invariant. In 1989, Yann LeCun turned the theoretical idea of Neocognitron into a practical one called LeNet-5 [30]. LeNet-5 was the first CNN developed for recognizing handwritten digits. LeCun et al. used back propagation [31][9] algorithm to train his CNN. The invention of LeNet-5 paved the way for the continuous success of CNN in various high-level computer vision tasks as well as motivated researchers to explore the capabilities of such networks for pixel-level classification problems like image segmentation. The key advantage of CNN over traditional machine learning methods is the ability to learn appropriate feature representations for the problem at hand in an end-to-end training fashion instead of using hand-crafted features that require domain expertise.

In this paper, we have tried to give a survey of different image segmentation models based on CNN. Basically, semantic segmentation and instance segmentation of an image are discussed. Herein, we have described architectural details of different state-of-the-art image segmentation models. Also, different aspects of those models are presented in tabular form for clear understanding.

1.1. Contributions of this paper

- Giving taxonomy and survey of the evolution of CNN based semantic and instance segmentation work of an image.

- Exploring elaborately some popular state-of-the-art segmentation models.
• Comparing training details of those models to have a clear view of hyper-parameter tuning.

• Comparing the performance metrics of those state-of-the-art models on different datasets.

1.2. Organization of the Article

Starting from the introduction in section 1, the paper is organized as follows: In section 2, we have given background details of our work. In sections 3 and 4, semantic segmentation and instance segmentation works are discussed respectively with some subsections. In section 5, Panoptic segmentation is presented in brief. The paper is concluded in section 6.

2. Background Details

2.1. Image Segmentation

In computer vision, image segmentation is a way of segregating a digital image into multiple regions according to the different properties of pixels. Unlike classification and object detection, it is typically a low level or pixel level vision task as the spatial information of an image is very important for segmenting different regions semantically. Segmentation aims to extract meaningful information for easier analysis. In this case the image pixels are labeled in such a way that every pixel in an image share certain characteristics such as color, intensity, texture etc. Mainly, image segmentation is of two types: semantic segmentation and instance segmentation. Also there is another type called panoptic segmentation\cite{32}, which is the unified version of two basic segmentation process. Figure 1 shows different types of semantic segmentation with example in figure 2.

![Figure 1: Different types of image segmentation](image-url)
2.2. Why CNN?

The task of segmenting an image is not a new field of computer vision. Various researchers are addressing this task in different ways using traditional machine learning algorithms with various techniques such as thresholding, region growing, edge detection, clustering, super-pixel etc for years. Most of the successful works are based on handcrafted machine learning features such as HOG, SIFT, etc. First of all, feature engineering needs domain expertise and the success of those machine learning based models was slowed down around the era when deep learning was started to take over the world of computer vision which only needs data. Among different deep learning algorithms, CNN got tremendous success in different fields of computer vision as well as grabbing the area of image segmentation.

3. Semantic Segmentation

Semantic segmentation describes the process of associating each pixel of an image with a class label. Figure 3 shows the process of semantic segmentation. After 2012, we have got different successful semantic segmentation models based on CNN. In this section, we are going to survey the evolution
of CNN based semantic segmentation models. In addition, we are going to bring up here an elaborate exploration of some state-of-the-art models.

3.1. Evolution of CNN based Semantic Segmentation Models:

Application of CNN in semantic segmentation models has started with a huge diversity. In [58], the authors have used multi-scale CNN for scene labeling and achieves state-of-the-art result in the Sift flow [59], the Barcelona dataset [60] and the Stanford background dataset [61]. R-CNN [62] used selective search [63] algorithm to extract region proposals first and then applied CNN upon each proposal for PASCAL VOC semantic segmentation challenge [64]. R-CNN achieved record result over second order pooling ($O_2P$) [65] which was a leading hand engineered semantic segmentation system at that time. At the same time, Gupta et al. [55] used CNN along with geocentric embedding on RGB-D images for semantic segmentation.

Among different CNN based semantic segmentation models Fully Convolutional Network (FCN) [66] as discussed in section 3.2.1 gained the maximum attention and a FCN based semantic segmentation model trend has been emerged. Major changes in FCN which helped the model to achieve state of the art result are the base model VGG16, bipolar interpolation technique for up-sampling the final feature map and skip connection for combining low layer and high layer features in the final layer for fine grained semantic segmentation. FCN have used only local information for semantic segmentation but only local information makes semantic segmentation quite ambiguous. To reduce ambiguity contextual information from the whole image is much helpful. In [67] and [68] authors have used contextual features and achieved state of the art performance.

Chen et al aggregate ‘atrous’ algorithm and conditional random (CRF) field in semantic segmentation and proposed DeepLab [69] as discussed in section 3.2.2. Later the authors have incorporate ‘Atrous Special Pyramid
Pooling (ASPP)’ in DeepLabv2 [70]. DeepLabv3 [71] has gone further and used cascaded deep ASPP module to incorporate multiple context. All three version of DeepLab have achieved good results.

Deconvnet [72] used convolutional network followed by hierarchically opposite de-convolutional network for semantic segmentation as discussed in section 3.2.3. Ronneberger et al used a U-shaped network called U-Net [73] which has a contracting and an expansive pathway to approach semantic segmentation. Contracting path extracts feature maps and reduces spatial information as traditional convolution network. Expansive pathway take the contracted feature map as input and apply an up-convolution. In each step of expansive pathway, the network concatenate the reduced up-convolved feature map with the corresponding cropped feature map from contracting pathway. In this way, U-Net incorporate both high level feature and low level spatial information together for more precise segmentation. Section 3.2.4 discussed the model in more detail. SegNet [74] is a encoder decoder network for semantic segmentation. Encoder is a basic VGG16 network excluding FC layers. Decoder is identical to encoder but the layers are hierarchically opposite. Decoder used convolution and unpooling operation to get a feature map of size similar to input image for precise localization of segmented object. SegNet is discussed in section 3.2.7. The basic architectural intuition of U-Net, Deconvnet and SegNet are similar except some individual modification. The second half of those architectures is the mirror image of first half.

Liu et al mixed the essence of global average pooling and L2 normalization layer in FCN [66] architecture, and proposed ParseNet [75] to achieve state of the art result in various datasets. Zhao et al. proposed Pyramid Scene Parsing Network(PSPNet) [76]. They have used Pyramid Pooling Module on top of the last extracted feature map to incorporate global contextual information for better segmentation. Peng et al used the idea of global convolution using large kernel to apply the advantage of both local and global features [77]. Pyramid Attention Network (PAN) [78], ParseNet [75], PSPNet [76] and GCN [77] have used global context information with local feature to have better segmentation. Sections 3.2.6, 3.2.9 and 3.2.8 will discuss those models in detail.

Fully convolutional DenseNet [8] is used to address semantic segmentation in [79, 80]. DeepUNet [81], a ResNet based FCN, used to segment sea land. At the same time, ENet [82], ICNet [83] are used as real time semantic segmentation model for autonomous vehicle. Some recent works [84, 85, 86]
has used combination of encoder-decoder architecture and dilated convolution for better segmentation. Kirillov et al.\cite{87} used point based rendering in DeepLabV3\cite{71} and in semanticFPN \cite{88} and produce state-of-the art semantic segmentation model.

3.2. Some popular state-of-the-art semantic segmentation models:

In this section, we are going to explore architectural details of some state of the art CNN based semantic segmentation models in detail.

3.2.1. FCN:

Long et al. proposed the idea of Fully Convolutional Network(FCN)\cite{66} to address the semantic segmentation task. They have used AlexNet\cite{4}, VGGNet\cite{6} and GoogleNet\cite{7}, pre-trained on ILSVRC\cite{89} data, as base model. They transferred these models from classifier to dense FCN by substituting fully connected layers with $1 \times 1$ convolutional layers and append a $1 \times 1$ convolution with channel dimension 21 to predict scores for each of the PASCAL VOC\cite{90} class (including background). This process produces

Figure 4: Architecture of FCN32s, FCN16s, FCN8s

a class presence heat map in low resolution. The authors have experienced that among FCN-AlexNet, FCN-VGG16 and FCN-GoogLeNet, FCN-VGG16 gave the highest mean IU(56.0 %) on PASCAL VOC 2011 validation dataset. So they choose FCN-VGG16 network for further experiment. As the network produces coarse output locations, the authors used bilinear interpolation to up-sample the coarse output 32$x$ to make it pixel dense. But this
up-sampling was not enough for fine-grained segmentation. So the authors used skip connection \[91\] to combine final prediction layer and feature rich lower layers of VGG16 and call this combination as *deep jet*. Figure 4 shows different *deep jet*: FCN-16s and FCN-8s and FCN-32s. The authors have shown that FCN-8s gave the best result in PASCAL VOC 2011 & 2012 \[90\] test dataset and FCN-16s gave the best result on both NYUDv2 \[92\] & SIFT Flow \[59\] datasets.

### 3.2.2. DeepLab:

Chen et al. has brought together methods from Deep Convolutional Neural Network (DCNN) and probabilistic graphical model, and produced DeepLab \[69\] to address semantic segmentation. DeepLab achieved 71.6% IOU accuracy in the test set of the PASCAL VOC 2012 semantic segmentation task. The authors have faced two technical difficulties in the application of DCNN to semantic segmentation: down sampling and spatial invariance. To handle the first problem, the authors have employed ‘atrous’ (with holes) \[93\] algorithm for efficient dense computation of CNN. Figure 5a and 5b shows atrous algorithm in 1-D and in 2-D. To handle second problem, they have applied fully connected pair wise conditional random field (CRF) to capture fine details. In addition, the authors have reduced the size of the receptive field 6× than the original VGG16 \[6\] network to reduce the time consumption of the network and also used multi-scale prediction for better boundary localization. The authors again modified the DeepLab using

![Atrous algorithm illustration](image)

**Figure 5**: Illustration of atrous algorithm (a) in 1-D, when kernel size=3, input-stride=2 and output-stride=1 \[69\] and (b) in 2-D, when kernel size 3 × 3, with rate 1, 6 and 24 \[71\]

Atrous Special Pooling Pyramid (ASPP) to aggregate multi-scale feature for better localization and proposed DeepLabv2 \[70\]. Figure 6 shows ASPP. This architecture used both ResNet \[8\] and VGGNet \[6\] as base network. In DeepLabv3 \[71\], to incorporate multiple context in the network, the authors
have used cascaded modules and have gone deeper specially with ASPP module.

![figure](image)

**Figure 6: Atrous Spatial Pooling Pyramid [71]**

### 3.2.3. Deconvnet:

Deconvnet [72] proposed by Noh et al. has convolutional and de-convolutional network. The convolutional network is topologically identical with the first 13 convolution layers and 2 fully connected layers of VGG16 [6] except the final classification layer. As in VGG16, pooling and rectification layers are also added after some of the convolutional layers. De-convolutional network is identical to convolutional network but hierarchically opposite. It also has multiple series of deconvolution, un-pooling and rectification layers. All the layers of convolutional and de-convolutional network extracts feature maps except the last layer of de-convolutional network which generates pixel wise class probability map of same size as input image. In de-convolutional network, the authors have applied un-pooling which is the reverse operation of pooling of convolutional network to reconstruct the original size of activation. Following [5] [94], un-pooling is done using max-pooling indices which is stored at the time of convolution operation in convolutional network. To densify enlarged but sparse un-pooled feature maps, convolution like operation is done using multiple learned filters by associating single input activation with multiple outputs. Unlike FCN, the authors applied their network on object proposals extracted from the input image and produced pixel wise prediction. Then they have aggregated outputs of all proposals to the original image space for segmentation of whole image. This instance wise segmentation approach handles multi-scale object with fine detail and also reduces training complexity as well as memory consumption for training. To handle internal covariate shift in the network, the authors have added batch normal-
ization layer on top of convolutional and de-convolutional layers. The architecture of Deconvnet is shown in figure 7.

![Convolution-Deconvolution Architecture](image)

Figure 7: Convolution-Deconvolution architecture of Deconvnet

### 3.2.4. U-Net:

U-Net is a U-shaped semantic segmentation which has a contracting path and an expansive path. Every step of contracting path consists of two consecutive $3 \times 3$ convolutions followed by ReLU nonlinearity and max pooling using $2 \times 2$ window with stride 2. During the contraction, the feature information is increased while spatial information is decreased. On the other hand, every step of expansive path consists of up-sampling of feature map followed by a $2 \times 2$ up-convolution. This reduces the feature map size by a factor of 2. Then the reduced feature map is concatenated with the corresponding cropped feature map from the contracting path. Then two consecutive $3 \times 3$ convolution operations are applied followed by ReLU nonlinearity. In this way the expansive pathway combines the features and spatial information for precise segmentation. The architecture of U-Net is shown in figure 8.

![U-Net Architecture](image)

Figure 8: U-Net Architecture

### 3.2.5. Dialatednet:

Traditional CNN, used for classification tasks, looses resolution in its way and it is not suitable for dense prediction. Yu and Koltun have introduced a modified version of traditional CNN, called dialated convolution or DialatedNet, to accumulate multi-scale contextual information systematically for better segmentation without suffering the loss of resolution. DialatedNet is like a rectangular prism of convolutional layers unlike conventional pyramidal CNN. Without losing any spatial information, it can support exponential expansion of receptive fields as shown in figure 9.
3.2.6. ParseNet:

Liu et al proposed an end-to-end architecture called ParseNet [75] which is an improvement of Fully Convolution Neural Network. The authors have added global feature or global context information for better segmentation. In figure 10, the model description of ParseNet is shown. Till convolutional feature map extraction, the ParseNet is same as FCN [66]. After that the authors have used global average pooling to extract global contextual information. Then the pooled feature maps are un-pooled to get the same size as input feature maps. Now, the original feature maps and un-pooled feature maps are combined for predicting final classification score. As the authors have combined two different feature maps from two different layer of the network, those feature maps would be different in scale and norm. To make the combination work, they have used two L2 normalization layers: one after global pooling and another after original feature map extracted from FCN simultaneously. This network achieved state-of -the-art performance on ShiftFlow [59], PASCAL-context [97] and near the state of the art on PASCAL VOC 2012 dataset.
3.2.7. SegNet:

SegNet [74] has encoder-decoder architecture followed by final pixel wise classification layer. The encoder network has 13 convolutional layers as in VGG16 [6] and corresponding decoder part also has 13 de-convolutional layers. The authors did not use fully connected layers of VGG16 to retain the resolution in the deepest layer and also to reduce the number of parameters from 134M to 14.7M. In each layer in the encoder network, a convolutional operation is performed using filter bank to produce feature maps. Then, to reduce internal covariate shift the authors have used batch normalization [98] [99] followed by ReLU [100] nonlinearity operation. Resulting output feature maps are max-pooled using a $2 \times 2$ non-overlapping window with stride 2 followed by a sub-sampling operation by a factor of 2. Combination of max-pooling and sub-sampling operation achieves better classification accuracy but reduces the feature map size which leads to lossy image
representation with blurred boundaries which is not ideal for segmentation purpose where boundary information is important. To retain boundary information in the encoder feature maps before sub-sampling, SegNet stores only the max-pooling indices for each encoder map. For semantic segmentation, output image resolution should be same as input image. To achieve this, SegNet does up-sampling in its decoder using the stored max-pooling indices from the corresponding encoder feature map resulting high resolution sparse feature map. To make the feature maps dense, convolution operation is performed using trainable decoder filter bank. Then the feature maps are batch normalized. The high resolution output feature map produced form final decoder are fed into trainable multi-class softmax classifier for pixel wise labeling. The architecture of SegNet is shown in figure 11.

Figure 11: Encoder-decoder architecture of SegNet[74]

3.2.8. GCN:
Like ParseNet, Global Convolution Network [77] has also used global features along with local features to make the pixel-wise prediction more accurate. The task of semantic segmentation is the combination of classification and localization. These two tasks are contradictory in nature. Classification should be transformation invariant and localization should be transformation sensitive. Previous state-of-the-art models focused on localization more than classification. In GCN, the authors did not use any fully connected layers or global pooling layers to retain spatial information. On the other hand, they have used large kernel size (global convolution) to make their network transformation invariant in case of pixel-wise classification. To refine the boundary further the authors have used Boundary Refinement (BR) block. As shown in figure [12] ResNet is used as backbone. GCN module is inserted in the network followed by BR module. Then score maps of lower resolution
are up-sampled with a deconvolution layer, and then added up with higher ones to generate new score maps for final segmentation.

3.2.9. **PSPNet:**

Pyramid Scene Parsing Network (PSPNet) [76], proposed by Zhao et al., has also used global contextual information for better segmentation. In this model, the authors have used Pyramid Pooling Module on top of the last feature map extracted using dilated FCN. In Pyramid Pooling Module, feature maps are pooled using 4 different scales corresponding to 4 different pyramid levels each with bin size $1 \times 1$, $2 \times 2$, $3 \times 3$ and $6 \times 6$. To reduce dimension, the pooled feature maps are convolved using $1 \times 1$ convolution layer. The outputs of the convolution layers are up-sampled and concatenated to the initial feature maps to finally contain the local and the global contextual information. Then, they are again processed by a convolutional layer to generate the pixel-wise predictions. In this network, the pyramid pooling module observes the whole feature map in sub-regions with different location. In this way the network understands a scene better which also leads to better semantic segmentation. In figure 13, the architecture of PSPNet is shown.
3.2.10. FC-DenseNet:

DenseNet \cite{8} is a CNN based classification network which contains only a down-sampling pathway for recognition. Jégou et al. \cite{101} has extended DenseNet by adding an up-sampling pathway to regain full resolution of the input image. To construct the up-sampling pathway, the authors followed the concept of FCN. They have referred the down-sampling operation of DenseNet as Transition Down (TD) and up-sampling operation in extended DenseNet as Transition UP (TU) as shown in figure 14. Rest of the convolutional layers follows the sequence of Batch Normalization, ReLU, 3 × 3 convolution and dropout of 0.2 as shown in top right block in figure 14. The up-sampling pathway used the sequence of dense block \cite{8} instead of convolution operation of FCN and transposed convolution as up-sampling operation. The up-sampling feature maps are concatenated with the feature maps derived from corresponding layers of down-sampling pathway. In figure 14 this long skip connections are shown in yellow circle.

3.2.11. Gated-SCNN:

Takikawa et al. proposed Gated - Shape CNN(GSCNN) \cite{80} for semantic Segmentation. As shown in figure 15, GSCNN consists of two streams of networks: regular stream and shape stream. Regular stream is a classical CNN for processing semantic region information. Shape stream consists of multiple Gated Convolution Layer (GCL) which process boundary information of regions using low level feature maps from regular stream. Outputs of both streams are fed into a fusion module. In fusion modules both outputs are combined using Atrous Special Pyramid Pooling \cite{70} module. Use of ASPP helps their model to preserve multi-scale contextual information. Finally, the Fusion module produced semantic region of objects with refined boundary.
Figure 14: Architecture of Fully Convolutional DenseNet for semantic segmentation with some building blocks [101]

Figure 15: Architecture of Gated Shape CNN for semantic segmentation [80]
3.3. Discussion

From the year 2012, different CNN based semantic segmentation model have been emerged in successive years till date. In subsection 3, we have described major up gradation in the networks of various state-of-the-art models for better semantic segmentation. Among different models, Fully Convolutional Network (FCN) set a path for semantic segmentation. Various models has used FCN as their base model. DeepLab and its versions have used atrous algorithm in different ways. SegNet, DeconvNet, U-Net have similar architecture where the second part of those architectures is hierarchically opposite of the first half. ParseNet, PSPNet and GCN have addressed semantic segmentation with respect to contextual information. FCDenseNet used top down /bottom up approach to incorporate low level features with high level features. So, the performance of a semantic segmentation model depends on internal architecture of a network as well as other aspects such as size of the data set, number of semantically annotated data, different training hyper parameters (Learning Rate, Momentum, weight Decay), Optimization algorithm, loss function etc. In this section, we have given different comparative aspects of each model in tabular form.

3.3.1. Optimization Details of Different State-of-the-art Semantic Segmentation Models:

Table 1 shows different optimization details of different models where we can see that the success of a model not only depends on the architecture. Table 2 presents base network (pre-trained on ImageNet [102] dataset), data pre-processing technique (basically data augmentation) and different loss function used for different models. Table 3 has briefly shown some important features of each model.

3.3.2. Comparative Performance of State-of-the-art Semantic Segmentation Models:

In this section, we are going to show comparative result of different state-of-the-art semantic segmentation models in different dataset. The performance metric used here is mean average precision (mAP) as Intersection over union(IoU) threshold.

4. Instance Segmentation

Like semantic segmentation, the applicability of CNN has been spread over instance segmentation too. Unlike semantic segmentation, instance seg-
Table 1: Optimization details of different state-of-the-art semantic segmentation models

| Name of the model | Optimization Algorithm | Mini Batch Size | Learning Rate | Momentum | Weight Decay |
|-------------------|------------------------|-----------------|---------------|----------|--------------|
| FCN-VGG16 [66]    | SGD [103]              | 20 images       | 0.0001        | 0.9      | 0.0016 or 0.0625 |
| DeepLab [69]      | SGD                    | 20 images       | initially 0.001 (0.01 for final classification layer), increasing it by 0.1 at every 2000 iteration. | 0.9      | 0.0005 |
| DeconvNet [72]    | SGD                    | -               | 0.01          | 0.9      | 0.0005 |
| U-Net [73]        | SGD                    | single image    | 0.001         | 0.9      | -            |
| DialatedNet [56]  | SGD                    | 14 images       | 0.001         | 0.9      | -            |
| ParseNet [75]     | SGD                    | 1e − 9          | 0.9           |          |              |
| SegNet [74]       | SGD                    | 12 images       | 0.1           | 0.9      |              |
| GCN [77]          | SGD                    | Single image    | 1e − 4        | 0.9      | 0.0005 |
| PSPNet [76]       | SGD                    | 16 images       | 'poly' learning rate with base learning rate of 0.01 and power to 0.9 | 0.9      | 0.0001 |
| FC-DenseNet103 [101] | SGD                   | 1e − 3 with an exponential decay of 0.995 | 0.9          | 1e − 4 |
| Gated-SCNN [80]   | SGD                    | 16              | 1e − 2 with polynomial decay policy | 0        |              |

mentionation masks each instance of an object contained in an image independently. The task of object detection and instance segmentation are quite correlated. In object detection, researchers use bounding box to detect each object instances of an image with a label for classification. Instance segmentation put this task one step forward and put a segmentation mask for each instance.

Concurrent to semantic segmentation research, instance segmentation research has also started to use convolutional neural network(CNN) for better segmentation accuracy. Herein, we are going to survey the evolution of CNN based instance segmentation models. In addition, we are going to bring up here an elaborate exploration of some state-of-the-art models for instance segmentation task.
Table 2: Base Model, data preprocessing technique and loss functions of different Stat-of-the-art semantic segmentation models.

| Name of the model | Base Network | Data pre-processing | Loss Function |
|-------------------|--------------|---------------------|---------------|
| FCN-VGG16         | AlexNet [46], VGGNet [6], GoogLeNet [7] (All pre-trained on ImageNet [8]) | Data augmentation using extra annotated data of [106] | Per-pixel multinomial logistic loss |
| DeepLab [69]      | VGG16 [6] pre-trained on ILSVRC dataset | Data augmentation using extra annotated data of [106] | Sum of cross-entropy loss |
| DeeplabV3 [72]    | VGG16 pre-trained on ILSVRC dataset | Data augmentation using extra annotated data of [106] | Cross entropy loss |
| U-Net [73]        | FCN [66] | Data augmentation by applying random elastic deformation to the available training images | Semantic Boundaries Dataset [106] is used as auxiliary dataset |
| ParseNet [75]     | FCN [66] | Data augmentation using extra annotated data of [106] | Cross entropy loss |
| SegNet [74]       | VGG16 [6] | Local contrast normalization to RGB data | Four losses:  
|                   |              |                      |  
|                   |              |  - Additional loss for initial result generation  
|                   |              |  - Final loss for learning the residue later  
|                   |              |  - Auxiliary loss for shallow layers  
|                   |              |  - Master branch loss for final prediction  
| GCN [77]          | ResNet152 [6] as feature network and FCN-4 [66] as segmentation network | Semantic Boundaries Dataset [106] is used as auxiliary dataset | Cross entropy loss |
| PSPNet [76]       | Pretrained ResNet [6] | Data augmentation: random mirror and random resize between 0.5 and 2, random rotation between -10 and 10 degrees, random Gaussian blur | Four losses:  
|                   |              |  - Additional loss for initial result generation  
|                   |              |  - Final loss for learning the residue later  
|                   |              |  - Auxiliary loss for shallow layers  
|                   |              |  - Master branch loss for final prediction  
| FC-DenseNet [101] | DenseNet [6] | Data augmentation using random cropping and vertical flipping |  
| Gated-SCNN [80]   | ResNet101 [6] and WideResNet [106] |  
|                   |              |  - Segmentation loss for regular stream  
|                   |              |  - Dual task loss for shape stream  
|                   |              |  - Standard binary cross entropy loss for boundary refinement  
|                   |              |  - Standard cross entropy for semantic segmentation  

4.1. Evolution of CNN based Instance Segmentation Models:

CNN based instance segmentation has also started its journey along with semantic segmentation. As we have mentioned in section 4 that instance segmentation task only adds a segmentation mask to the output of object detection task. That is why most of the CNN based instance segmentation models have used different CNN based object detection models to produce better segmentation accuracy and to reduce test time.

Hariharan et al. have followed the architecture of R-CNN [62] object detector and proposed a novel architecture for instance segmentation called Simultaneous Detection and Segmentation (SDS) [112], which is a 4 step instance segmentation model as described in section 4.2.1.
Table 3: Some important features of different state-of-the-art semantic segmentation models

| Model            | Important Features                                                                 |
|------------------|-------------------------------------------------------------------------------------|
| FCN-VGG16        | • Dropout is used to reduce overfitting                                              |
|                  | • End to end trainable                                                              |
| DeepLab          | • End to end trainable                                                              |
|                  | • Piecewise training for DCNN and CRF                                               |
|                  | • Inference time during testing is 8 frame per second                                |
|                  | • Used Atrous Special Pyramid Pooling module for aggregating multi-scale features   |
| Deconvnet        | • Used edge-box to generate region proposal                                          |
|                  | • Used Batch Normalization to reduce internal covariate shift and remove dropout     |
|                  | • Two-stage training for easy examples and for more challenging examples            |
|                  | • End to end trainable                                                              |
|                  | • Drop-out layer is used at the end of the contracting path                         |
| U-Net            | • End to end trainable                                                              |
|                  | • Inference time for testing was less than 1 sec per image                           |
| DialatedNet      | • Two stage training:                                                               |
|                  | • Front end module with only dilated convolution                                    |
|                  | • Dilated convolution with multi-scale context module                               |
| ParseNet         | • End to end trainable                                                              |
|                  | • Batch Normalization is used                                                       |
|                  | • Drop-out of 0.5 is used in deeper layers                                          |
| SegNet           | • Different Ablation study                                                          |
| GCN              | • Large Kernel Size                                                                 |
|                  | • Included Global Contextual information                                            |
| PSPNet           | • End to end training                                                               |
|                  | • Contains dilated convolution                                                     |
|                  | • Batch normalization                                                              |
|                  | • Used pyramid pooling module for aggregating multi-scale features                  |
| FC-DensNet       | • Initialized the model with HeUniform and trained it with RMSprop                  |
|                  | • Used dropout of 0.2                                                               |
|                  | • Used the model parameters efficiently                                             |
| Gated -SCNN      | • End to end trainable                                                              |
|                  | • Applied ablation study                                                           |

Till this time CNN based models have only used last layer feature map for classification, detection and even for segmentation. In 2014, Hariharan et al. have again proposed a concept called Hyper-column [113] which has used the information of some or all intermediate feature maps of a network for better instance segmentation. The authors added the concept of Hyper-column to SDS and their modified network achieved better segmentation accuracy.

Different object detector algorithm such as R-CNN, SPPnet [15], Fast R-CNN [16] have used two stages network for object detection. First stage detects object proposals using Selective Search [63] algorithm and second stage classify those proposals using different CNN based classifier. Multi-box [114, 115], Deepbox [116], Edgebox [117] have used CNN based proposal generation method for object detection. Faster R-CNN [17] have used CNN
Table 4: Comparative accuracy of different semantic segmentation models in terms of mean average precision (mAP) as Intersection over Union (IoU)

| Model       | Year | Used Dataset                                      | mAP as IoU |
|-------------|------|---------------------------------------------------|------------|
| FCN-VGG16 [66] | 2014 | Pascal VOC 2012 [64]                              | 62.2%      |
| DeepLab [69]  | 2014 | Pascal VOC 2012                                   | 71.6%      |
| Deconvnet [72] | 2015 | Pascal VOC 2012                                   | 72.5%      |
| U-Net [73]    | 2015 | ISBI cell tracking challenge 2015                 | 72.5%      |
| DeepLab [69]  | 2014 | Pascal VOC 2012                                   | 71.6%      |
| Deconvnet [72] | 2015 | Pascal VOC 2012                                   | 72.5%      |
| U-Net [73]    | 2015 | ISBI cell tracking challenge 2015                 | 72.5%      |
| ParseNet [75] | 2016 | • ShiftFlow [69]                                  | 40.4%      |
|              |      | • PASCAL- Context [97]                            | 36.64%     |
|              |      | • Pascal VOC 2012                                 | 69.8%      |
| SegNet [74]   | 2016 | • CamVid road scene segmentation [108]            | 60.10%     |
|              |      | • SUN RGB-D indoor scene segmentation [109]       | 31.84%     |
| GCN [77]      | 2017 | • PASCAL VOC 2012                                 | 82.2%      |
|              |      | • Cityscapes [110]                                | 79.9%      |
| PSPNet [76]   | 2017 | • PASCAL VOC 2012                                 | 85.4%      |
|              |      | • Cityscapes [110]                                | 80.2%      |
| FC-DenseNet103 [101] | 2017 | • CamVid road scene segmentation                  | 69.9%      |
|              |      | • Gatech [111]                                    | 79.4%      |
| Gated-SCNN [80] | 2019 | • Cityscapes [110]                                | 82.8%      |

Based ‘region proposal network (RPN)’ for generating box proposal. However, the mode of all these proposal generation is using bounding box and so the instance segmentation models. In parallel to this, instance segmentation algorithm such as SDS and Hyper column have used Multi-scale Combinatorial Grouping (MCG) [118] for region proposal generation. DeepMask [119], as discussed in section 4.2.2, has also used CNN based RPN as Faster R-CNN to generate region proposals so that the model can be trained end to end.

Previous object detection and instance segmentation modules such as [62, 15, 16, 17, 112, 113, 119] etc. have used computationally expensive external methods for generating object level or mask level proposals like Selective Search, MCG, CPMC [65], RPN etc. Dai et al. [120] break the tradition of using pipeline network and did not use any external mask proposal method. The authors have used a cascaded network for incorporating features from different CNN layers for instance segmentation. Also, sharing of convolution features lead to faster segmentation models. Details of the network is discussed in section 4.2.3.

In papers [121, 122, 68, 15, 123, 113, 66, 124] researchers used contextual information and low level features into CNN in various ways for better segmentation. Zagoruko et al. [125] has also used those ideas by
integrating skip connection, foveal structure and integral loss in Fast R-CNN [16] for better segmentation. Further description is given in section 4.2.4.

SDS, DeepMask, Hyper-columns has used feature maps from top layers of the network for object instance detection which leads to coarse object mask generation. Introduction of skip connection in [126, 127, 128, 125] reduces the coarseness of masks which is more helpful for semantic segmentation rather instance segmentation. Pinheiro et. al [129] have used their model to generate coarse feature map using CNN and then refined those model to get pixel accurate instance segmentation mask using a refinement model as described in section 4.2.5.

Traditional CNNs are translation invariant i.e images with same properties but with different contextual information will score same classification score. Previous models, specially FCN, used single score map for semantic segmentation. But for instance segmentation, a model must be translation variant so that same image pixel of different instances having different contextual information can be segmented separately. Dai et al [19] integrated the concept of relative position into FCN to distinguish multiple instances of an object by assembling small set of score maps computed from different relative position of an object. Li et al [130] extended the concept of [19] and introduced two different position-sensitive score maps as described in section 4.2.7. SDS, Hypercolumn, CFM [131], MNC [120], MultiPathNet [125] used two different subnetworks for object detection and segmentation which prevent the models to become end to end trainable. On the other hand [132, 133] extends instance segmentation by grouping or clustering FCNs score map which involves a large amount of post processing. [130] introduced a joint formulation of classification and segmentation masking subnets in an efficient way.

While [134, 135, 136, 137] have used semantic segmentation models, Mask R-CNN [15] extends the object detection model Faster R-CNN by adding a binary mask prediction branch for instance segmentation.

The authors of [138, 139] has introduced direction feature to predict different instances of a particular object. [138] has used template matching technique with direction feature to extract center of an instance where as [139] followed the assembling process of [130, 19] to get instances.

[140, 141, 135, 113] have used features form intermediate layers for better performance. Liu et al. [142] have also used the concept of feature propagation from lower level to top level and built a state-of-the-art model based on Mask R-CNN as discussed in section 4.2.10.
Object detection using sliding window approach gave us quite successful work such as Faster R-CNN, Mask R-CNN etc. with refinement step and SSD[21], RetinaNet[24] without using refinement stage. Though, sliding window approach is popular in object detection but it was missing in case of instance segmentation task. Chen et al. [143] have introduced dense instance segmentation to fill this gap and introduced TensorMask. Recently, Kirillov et al. [87] used point based rendering in Mask R-CNN and produce state-of-the-art instance segmentation model.

4.2. Some State-of-the-art Instance Segmentation Models:

In this section, we are going to elaborate discuss about some state of the art CNN based instance segmentation models.

4.2.1. SDS:

Simultaneous Detection and Segmentation (SDS) [112] model consists of 4 steps for instance segmentation. The steps are proposal generation, feature extraction, region classification and region refinement respectively. On input image the authors have used Multi-scale Combinatorial Grouping(MCG) [118] algorithm for generating region proposals. Then each region proposals are fed into two CNN based sibling networks. As shown in figure 16 the upper CNN generates feature vector for bounding box of region proposals and the bottom CNN generates feature vector for segmentation mask. Two feature vectors are then concatenated and class scores are predicted using SVM for each object candidate. Then non maximum suppression is applied on the scored candidates to reduce the set of same category object candidates. Finally, to refine surviving candidates CNN feature maps are used for mask prediction.

![Architecture of SDS Network](image)
4.2.2. DeepMask:

DeepMask [119] used CNN to generate segmentation proposal rather than less informative bounding box proposal algorithms such as Selective Search, MCG etc. DeepMask used VGG-A[6] model (discarding last max pooling layer and all fully connected layers) for feature extraction. As shown in figure [17] the feature maps are then fed into two sibling branches. The top branch which is the CNN based object proposal method of DeepMask predicts a class-agnostic segmentation mask and bottom branch assigns a score for estimating the likelihood of patch being centered on the full object. The parameters of the network are shared between the two branches.

4.2.3. Multi-task Network Cascades (MNC):

Dai et al. [120] used a network with cascaded structure to share convolutional features and also used region proposal network (RPN) for better instance segmentation. The authors have decomposed the instance segmentation task into three subtasks: instance differentiation (class agnostic bounding box generation for each instance), mask estimation (estimated a pixel-level mask/instance) and object categorization (instances are labeled categorically). They proposed Multi-task Network Cascades (MNC) to address these sub-tasks in three different cascaded stages to share convolutional features. As shown in figure [18] MNC takes an arbitrary sized input which is a feature map extracted using VGG16 network. Then at the first stage, the network generates object instances from the output feature map as class agnostic bounding boxes with an objectness score using RPN. Shared convolutional features and output boxes of stage-1 then goes to second stage for regression of mask level class-agnostic instances. Again, shared convolutional features and output of previous two stages are fed into third stage for
generating category score for each instance.

Figure 18: Three stage architecture of Multi-task Network Cascades [120].

4.2.4. MultiPath Network:

Zagoruko et al. integrate three modifications in the Fast R-CNN object detector and proposed Multipath Network [125] for both object detection and segmentation tasks. Three modifications are skip connections, foveal structure and integral loss. Recognition of small objects without context is difficult. That is why, in [121], [122], [68], [15], [144], the researcher used contextual information in various ways in CNN based model for better classification of objects. In Multipath Network, the authors have used four contextual regions called foveal regions. The view size of those regions are $1 \times 1$, $1.5 \times 1.5$, $2 \times 2$, $4 \times 4$ of the original object proposal. On the other hand, researchers of [123], [113], [66], [124] has used feature from higher resolution layers of CNN for effective localization of small objects. In Multipath Network, the authors have connected third, fourth and fifth convolutional layers of VGG16 to the four foveal regions to use multi-scale features for better object localization. Figure 19 shows the architectural pipeline of MultiPath Network. Feature maps are extracted from an input image using VGG16 network. Then using skip connection those feature maps goes to four different Foveal Region. Output of those regions are concatenated for classification and bounding box regression. Use of DeepMask segmentation proposal helped their model to be the 1st runner-up in MS COCO 2015 [145] detection and segmentation challenges.
4.2.5. SharpMask:

DeepMask generates accurate mask for object level but the degree of alignment of the mask with the actual object boundary was not good. SharpMask [129] contains a bottom-up feed forward network for producing coarse semantic segmentation mask and a top down network to refine those mask using refinement module. The authors have used feed forward DeepMask segmentation proposal network with their refinement module and named it as SharpMask. As shown in figure 20, the bottom-up CNN architecture produces coarse mask encoding. Then the output mask encoding is fed into a top down architecture where a refinement module un-pool it using matching features from bottom-up module. This process continues until the reconstruction of full resolution image and the final object mask.

4.2.6. InstanceFCN:

Fully convolutional network is good for single instance segmentation of an object category. But it can not distinguish multiple instances of an object. Dai et al have used the concept of relative position in FCN and proposed instance sensitive fully convolutional network (InstanceFCN) [19] for instance segmentation. The relative position of an image is defined by a $k \times k$ grid on a square sliding window. This produces a set of $k^2$ instance sensitive score maps rather than one single score map as FCN. Then the instance sensitive score maps are assembled according to their relative position in a $m \times m$ sliding window to produce object instances. In DeepMask [119], shifting sliding window for one stride leads to generation of two different
fully connected channels for same pixel which is computationally exhaustive. In InstanceFCN, the authors have used the concept of local coherence [146] which means sliding a window does not require different computation for a single object. Figure 21 shows the architecture of InstanceFCN.

4.2.7. FCIs

InstanceFCN introduced position-sensitive score mapping to signify the relative position of an object instance but the authors have used two different subnetwork for object segmentation and detection. Because of two different network, the solution was not end to end. Li et al. [130] proposed first end to end trainable fully convolutional network based model in which segmentation and detection are done jointly and concurrently in a single network by score map sharing as shown in figure 22. Also instead of sliding window approach, the model used box proposals following [17]. The authors has used two different position-sensitive score maps: position sensitive inside score maps and position sensitive outside score maps. These two score maps depends on detection score and segmentation score of a pixel in a given region of interests(RoIs) with respect to different relative position. As shown in figure
RPN is used to generate RoIs. Then RoIs are used on score maps to detect and segment object instances jointly.

4.2.8. Mask R-CNN

Mask R-CNN contains three branches for predicting class, bonding-box and segmentation mask for instances with in a region of interest (RoI). This model is the extension of Faster R-CNN. As Faster R-CNN, Mask R-CNN contains two stages. In first Stage, it uses RPN to generate RoIs. Then to preserve the spatial location, the authors have used RoIAlign instead of RoIPool as in Faster R-CNN. In second stage, it simultaneously predicts class label, bounding box offset and binary mask for each individual RoI. In Mask
R-CNN, prediction of binary mask for each class was independent and it was not multi-class prediction.

![Figure 23: Architecture of Mask R-CNN][18]

4.2.9. MaskLab

MaskLab [139] has utilized the merits of both semantic segmentation and object detection to handle instance segmentation. The authors have used Faster R-CNN [17] (ResNet-101 [8] based) for predicting bonding boxes for object instances. Then they have calculated semantic segmentation score maps for labeling each pixel semantically and direction score maps for predicting individual pixels direction towards the center of its corresponding instance. Those score maps are cropped and concatenated for predicting a coarse mask for target instance. The mask is then again concatenated with hyper-column features [113] extracted from low layers of ResNet-101 and processed using a small CNN of three layers for further refinement.

4.2.10. PANet:

Flow of information in convolutional neural network is very important as the low level feature maps are information rich in terms of localization and the high level feature maps are rich in semantic information. Liu et al. focused on this idea. Based on Mask R-CNN and Feature Pyramid Network (FPN) [147], they have proposed a Path Aggregation Network (PANet) [142] for instance segmentation. PANet used FPN as its base network to extract features from different layers. To propagate low layer feature through the network, a bottom up augmented path is used. Output of each layer is
generated using previous layers high resolution feature map and a coarse map from FPN using a lateral connection. Then an adaptive pooling layer is used to aggregate features from all levels. In this layer, a RoIPooling layer is used to pool features from each pyramid level and element wise max or sum operation is used to fuse the features. As Mask R-CNN, the output of feature pooling layer goes to three branch for prediction of bounding box, prediction of object class and prediction of binary pixel mask.

4.2.11. TensorMask

Previous instance segmentation models used methods in which the objects are detected using bounding box then segmentation is done. Chen et al. have used dense sliding window approach instead of detecting object in a bounding box named TensorMask [143]. The main concept of this architecture is the
use of structured high-dimensional (4D) tensors to present mask over an object region. A 4D tensor is a quadruple of \((V,U,H,W)\). The geometric sub-tensor \((H,W)\) represents object position and \((V,U)\) represents relative mask position of an object instance. Like feature pyramid network, TensorMask has also developed pyramid structure, called tensorbipyramid over a scale-indexed list of 4D tensors to acquire the benefits of multi scale.

Table 5: Optimization details of different state-of-the-art instance segmentation models

| Name of the model | Optimization Algorithm | Mini Batch Size | Learning Rate | Momentum | Weight Decay |
|-------------------|------------------------|----------------|---------------|----------|--------------|
| DeepMask         | SGD                    | 32 images      | 0.001         | 0.9      | 0.0005       |
| MNC [120]        | SGD                    | 1 images per GPU, total 8 GPUs are used | 0.001 for 32k iteration, 0.0001 for next 8K iteration | -        | -            |
| MultiPath Network [123] | SGD              | 4 images, 1 image per GPU, each with 64 object proposals | initially 0.001, after 100k iterations, it was reduced to 0.0001 | -        | -            |
| SharpMask [129]  | SGD                    | 1e-3           | -             | -        | -            |
| InstanceFCN [19] | SGD                    | 8 images each with 256 sampled windows, 1 image/GPU | 0.001 for initial 32k iterations and 0.0001 for the next 8k. | 0.9      | 0.0005       |
| FCIs [130]       | SGD                    | 8 images/batch, 1 image per GPU | 0.001 for the first 20k and 0.0001 for the next 10k iterations | -        | -            |
| Mask R-CNN [18]  | SGD                    | 16 images/batch, 2 images per GPU | 0.02 for first 160k iteration and 0.002 for next 120k iterations | 0.0001   | 0.9          |
| PANet [142]      | SGD                    | 16 images      | 0.02 for 120k iterations and 0.002 for 40k iterations | 0.0001   | 0.9          |
| TensorMask [143] | SGD                    | 16 images, 2 images per GPU | 0.02 with linear warm-up of 1k iteration | 0.9      | 0.0005       |

4.3. Discussion:

In previous subsection 4.2, we have presented important architectural details of different state-of-the-art models. Among different models, some of them are based on object detection models such as R-CNN, Fast R-CNN, Faster R-CNN etc. Some models are based on semantic segmentation model such as FCN, U-Net etc. SDS, DeepMask, SharpMask, InstanceFCN are based on proposal generation. InstanceFCN, FCIs, MaskLab calculate position sensitive score maps for instance segmentation. PANet emphasized on feature propagation across the network. TensorMask used sliding window approach for dense instance segmentation. So, architectural differences help
Table 6: Base Model, data preprocessing technique and loss functions of different Stat-of-the-art models.

| Name of the model | Base Network | Data pre-processing | Loss Function |
|-------------------|--------------|---------------------|---------------|
| SDS               | VGG-A pretrained on ImageNet dataset | ● Randomly jitter ‘canonical’ positive examples for increasing the model’s robustness | Sum of binary logistic regression losses |
|                   |              | ● Applied translation shift, scale deformation and horizontal flip for data augmentation | ● One for each location of the segmentation network |
|                   |              |                     | ● Other for the objectness score |
| MNC               | VGG-16, ResNet-101 |                         | Unified loss function: |
|                   |              |                     | ● RPN loss for box regression/instance |
|                   |              |                     | ● Mask regression loss/instance |
|                   |              |                     | ● loss function for categorizing instances |
|                   |              |                     | ● Inference time per image is 1.4sec |
| MultiPath Network | Fast R-CNN   | Horizontal flip as data augmentation | Integral loss function: |
| SharpMask         | DeepMask     |                     | ● Integral log loss function for classification |
| InstanceFCN       | VGG-16, pretrained on ImageNet | Arbitray sized images are used for training with scale jittering following [15] | Logistic regression loss for predicting objectness score and segment instances |
| FCIs              | ResNet-101   |                     | Multi-Task loss: |
|                   |              |                     | ● log loss function for classification |
| Mask R-CNN        | Faster R-CNN based on ResNet |                     | ● L1 loss function for bounding box regression |
| MaskLab           | ResNet-101 based Faster R-CNN pre-trained on ImageNet |                     | ● Average binary cross entropy loss for mask prediction |
| PANet             | ResNet-50, ResNeXt-101 [149] based Mask R-CNN and also FPN | Scale jittering is used | Weighted sum of all task loss specially for mask, per-pixel binary classification loss is used. Focal loss is used to handle foreground background class imbal-

different models to achieve success in various instance segmentation dataset. On the other hand, fine tuning of hyper-parameters, data pre-processing methods, choice of loss function and optimization function etc are also played an important role behind the success of a model. In this subsections we are going to present some of those important feature in a comparative manner.

4.3.1. Optimization Details of State-of-the-art Instance Segmentation Models:

Training and optimization process is very crucial for a model to become successful. Most of the state-of-the art model used stochastic gradient de-
Table 7: Some important features of different state-of-the-art instance segmentation models

| Model       | Important Features                                                                 |
|-------------|------------------------------------------------------------------------------------|
| SDS         | • Used MCG to generate region proposals                                             |
|             | • Used segmentation data from SBD[104]                                              |
| DeepMask    | • The inference time in MS COCO is 1.6s per image                                    |
|             | • The inference time in PASCAL VOC 2007 is 1.2s per image                            |
| MNC         | • End to End trainable                                                             |
|             | • Convolutional feature sharing leads to reduction of test time of 360ms/image.      |
| Multi-path  | Network                                                                           |
|             | • Skip Connection for sharing feature among multiple levels                         |
|             | • Foveal structure to capture multi-scale object                                    |
|             | • Integrated loss function for improving localization                              |
|             | • DeepMask region proposal algorithm to generate region proposals                   |
|             | • Training time 500ms/image                                                         |
| SharpMask   | • Bottom-up/top-down approach                                                      |
|             | • DeepMask used in bottom-up network to generate object proposal                    |
|             | • Top-down network is stack of refinement model which aggregate features from       |
|             |   corresponding layers from bottom-up path                                          |
|             | • Two stage training: One for bottom-up and another for top-down network            |
| InstanceFCN | • A small set of score maps computed from different relative position of an image  |
|             |   patch are assembled for predicting the segmentation mask                          |
|             | • Applied ‘hole algorithm[69]’ in last three layers of VGGNet                      |
| FCIs        | • End to end trainable FCN based model                                              |
|             | • Based on position sensitive inside and outside score map                          |
|             | • Inference time 0.24 seconds/image                                                  |
| Mask R-CNN  | • RoIAlign layers are used instead of RoIPool layer to preserve special location    |
|             | • Inference time was 200 ms per frame                                               |
| MaskLab     | • Used atrous convolution to extract denser feature map to control output resolution |
|             | • End to end trainable model                                                        |
|             | • To cover 360 degree of an instance 8 directions are used with 4 number of distance|
|             |   quantization bins for direction pooling                                           |
| PANet       | • FPN is used as Backbone network                                                   |
|             | • Adaptive feature pooling layer is introduced                                      |
| TensorMask  | • Dense instance segmentation using sliding window approach                          |
|             | • The model works on 4D tensor                                                      |

scent(SGD) [148] as optimization algorithm with different initialization of corresponding hyper parameters such as mini-batch size, learning rate, weight decay, momentum etc. Table 5 shows those hyper-parameter in a comparative way. Different models has used different CNN based classification, Object detection and semantic segmentation model as their base network according to the availability. Its an open choice to the researchers to choose a base model (may be pre-trained on some dataset) according to their application domain. Most of the data preprocessing basically includes different data augmentation technique. Differences in loss function depend on the variation of the model architecture as shown in table 6. Table 7 is showing some important features of different models.
Table 8: Comparison of different instance segmentation models as average precision according to IoU threshold

| Model                  | Year | Used Dataset                      | mAP as IoU |
|------------------------|------|-----------------------------------|------------|
| SDS                    | 2014 | • PASCAL VOC 2011 ⃗→ • PASCAL VOC 2012 ⃗→ | 51.6%      |
| DeepMask               | 2015 | • PASCAL VOC ⃗→ • MS COCO         | 52.6%      |
| MNC                    | 2016 | • PASCAL VOC 2012 ⃗→ • MS COCO 2015 ⃗→ | 63.3% (on validation set) 39.7% on test – devset (both mAP@0.5 IoU threshold) |
| MultPath Network       | 2015 | MS COCO 2015 ⃗→                  | 25.0% (AP), 45.4% (AP@50), and 24.5% (AP@75) , all on test dataset. Superscripts of AP denotes IoU threshold |
| SharpMask + MPN [124] | 2016 | MS COCO 2015 ⃗→                  | 25.1% (AP), 45.8% (AP@50) and 24.8% (AP@75) , all on test dataset. Superscripts of AP denotes IoU threshold |
| InstanceFCN+MNC        | 2016 | PASCAL VOC 2012 validation dataset ⃗→ | 61.5% (mAP@0.5) and 43.0% (mAP@0.7) |
| FCIs                   | 2017 | • Pascal voc 2012 ⃗→ • MS COCO 2016 ⃗→ | 65.7% (mAP@0.5) and 52.1% (mAP@0.7) 59.9% (mAP@0.5) (ensemble) |
| Mask R-CNN             | 2017 | MS COCO                           | 60.0% (AP@50) and 39.4% (AP@75) , all on test dataset. Superscripts of AP denotes IoU threshold |
| MaskLab                | 2018 | MS COCO (test-dev) ⃗→             | 61.1% (mAP@0.5) and 40.4% (mAP@0.7) |
| PANet                  | 2018 | • MS COCO 2016 ⃗→ • MS COCO 2017 ⃗→ | 65.1% (AP@50) and 45.7% (AP@75) 69.5% (AP@50) and 51.3% (AP@75) , (Mask AP). Superscripts of AP denotes IoU threshold |
| TensorMask             | 2019 | MS COCO (test-dev) ⃗→             | 57.3% (AP), 59.5% (AP@50) and 39.5% (AP@75) Superscripts of AP denotes IoU threshold |

4.3.2. Comparative Performance of State-of-the-art Instance Segmentation Models:

Around 2014, concurrent to semantic segmentation task, CNN based instance segmentation models has also started gaining better accuracy in various data sets such as PASCAL VOC, MS COCO etc. In table 8, we have shown comparative performance of various state-of-the-art instance segmentation models on those dataset.

5. Panoptic Segmentation

Panoptic segmentation (PS) [32, 150, 85, 151, 152, 153] is the combination of semantic segmentation and instance segmentation. This is a new research area these days. In this task, we need to associate all the pixels in the image with a semantic label for classification and also identify the instances of a particular class. The output of a panoptic segmentation model will contain two channels: one for pixel’s label (semantic segmentation) and another for predicting each pixel instance (instance segmentation).
6. Conclusion

Convolutional neural network based image segmentation is a challenging work as it needs spatially variant features to preserve the context of a pixel for semantic labeling. Semantic segmentation categorizes each pixel with a semantic label whereas instance segmentation segments individual instances of objects contained in an image. The success of those models depend mostly on different network architecture. Except for that various other aspects such as choice of the optimization algorithm, the value of hyperparameters, data-preprocessing technique, choice of the loss function, etc. are also responsible for becoming a successful model. In our article, we have presented the evolution of image segmentation models based on CNN. We have elaborately explored some state of the art semantic and instance segmentation models along with their optimization details. Lastly, we have compared those models’ performance on different benchmark datasets. The application area of segmentation is vast. According to the requirement of the application area, any model can be applied using some domain specific fine-tuning.

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