Efficient Yet Deep Convolutional Neural Networks for Semantic Segmentation

Sharif Amit Kamran  
Center for Cognitive Skill Enhancement  
Independent University Bangladesh  
Dhaka, Bangladesh  
Email: sharifamit@iub.edu.bd

Muhammad Hasan  
Computational Intelligence Lab  
KAIST  
Daejeon, Republic of Korea  
Email: hasandoesit@kaist.ac.kr

Ali Shihab Sabbir  
Center for Cognitive Skill Enhancement  
Independent University Bangladesh  
Dhaka, Bangladesh  
Email: asabbir@iub.edu.bd

Abstract—Semantic Segmentation using deep convolutional neural network pose more complex challenge for any GPU intensive work, as it has to compute million of parameters resulting to huge consumption of memory. Moreover, extracting finer features and conducting supervised training tends to increase the complexity furthermore. With the introduction of Fully Convolutional Neural Network, which uses finer strides and utilizes deconvolutional layers for upsampling, it has been a go to for any image segmentation task. We propose two segmentation architecture transferring weights from the popular classification neural net VGG19 and VGG16 which were trained on Imagenet classification dataset, transform all the fully connected layers to convolutional layers, use dilated convolution for decreasing the parameters, moreover we add more finer strides and attach four skip architectures which are element-wise summed with the deconvolutional layers in steps. We train and test on different sparse and fine data-sets like Pascal VOC2012, Pascal-Context and NYUDv2 and show how better our model performs in this tasks. On the other hand our model consumes up to 10-20 percent and for upsampling[6] and element-wise summing the coarse segmentation mask. So for extracting those local fine features and giving finer output[4], [5]. Problem definition of the task in hand is to keep the global structure in contrast with the local context[4], [5]. Most of the time the local features tend to get lost in the training process and global context seems to dominate throughout the segmentation mask. So for extracting those local fine features for upsampling[6] and element-wise summing the coarse semantic information. Skip architectures were introduced[4], [5], [7], [8] with the preexisting FCN architecture. By using Skip architectures the image representation becomes more finer and less coarse.

The drawback for designing convolutional neural network with high level computing for object recognition or for pixel-wise classification seems to be the huge amount of memory required for the task. Firstly, orthodox ConvNets have rather large receptive fields because of their convolutional filters and generates coarse blob-like output map when it is redefined to produce pixel-wise segmentation[4]. Secondly, subsampling with maxpool in ConvNets diminishes the chance to get finer output[9]. Furthermore, similar labeling in neighboring pixels tends to get lost in deeper layers where the upsampling takes place. So visual consistency and retaining spatial feature is one of the essential job for producing sharp segmentation mask. Falling short of producing such fine output can result in poor object portrayal and patch-like false regions in the segmentation mask[9], [10], [11], [12].

Using finer strides[4] and replacing vanilla convolution with dilated convolution[5], [13] we can achieve better segmentation results while keeping the memory usage in check. Because with dilation we can increase the receptive fields exponentially[5] whereas the filter of the convolution remains the same. So with the expense of reducing the size of the filter and adding dilation between it, we can free up more memory for computing from the sixth convolutional layer in the FCN architecture which is the most expensive layer.

Adding more Skip architectures seems to increase memory usage for the whole end-to-end network, but because additional memory has been freed up by dilated convolutions[5], [13], we can use two extra skip architectures to upsample the local features from the first two convolutional layers. In a feed forward network the size of the representation changes with each convolutions and it is down sampled using pool, so the feature hierarchies have to be added with the upsampled[4], [6] pool in steps.

Our proposal in this paper is a efficient yet deep feed forward neural net for a strongly supervised image segmentation task. Our work tends to integrate both dilated and vanilla convolution to recreate a FCN architecture which generates better output while consuming less memory. In addition, we introduce four skip architectures which fetches more local information lost in the network in bottom layers, upsampling it to top layers and element-wise summing with the global feature map in steps producing better segmentation mask.
while keeping GPU memory consumption in check. Most importantly, with this change in architecture, the end-to-end deep network can be trained on any type of data while utilizing the usual back-propagation algorithm with more efficient and finer results. Our benchmark result for PASCAL VOC2012 reduced validation set meanIoU of 64.9 percent for Dilated FCN-2s-VGG19 compared to 63.9 percent of FCN-8s. Additionally, we evaluated the performance of our deep convNet on Pascal VOC 2012 test data set yielding meanIoU of 69 percent for FCN-2s-VGG19 and 67.6 percent for FCN-2s-VGG16.

2 Literature Review

Following section describe different procedures which has been proposed before for conducting semantic segmentation task using deep learning. Out of many approaches only few have been adopted for high computing pixel-wise segmentation.

Our proposed model was developed based on a particular neural net that was used for image classification task [2], [11], [3] and the weights were transferred from it [16], [17]. Transfer learning was seen being performed in classification task, afterwards it was applied to object detection tasks, lately it has been adopted for instance aware segmentation [18] and image segmentation models with a powerful classifier [19], [20], [7]. We redesign and redefine the architecture and perform fine-tuning to get more sparse and accurate prediction for semantic segmentation. Furthermore, we compare different models with our one and show how it is more efficient and effective for semantic segmentation jobs.

Multi-digit recognition with neural network [21], an extension of LeNet [22], was such work where erratic range of values for input was first witnessed. Though the task was ordained for one dimensional data, Viterbi decoding was sufficient for such task. Three years later convolutional neural network was elongated for two dimensional feature output for processing postal address data [23]. These historical breakthroughs were designed to conduct small yet powerful detection task. Additionally LeCun et al. [24] using fully convolutional inference developed a CNN for sparse multiple class segmentation of embryo. We have also seen FCNs being used in many recent deep layered nets for high level computation. Using Sliding window for integrated object detection and localization by Eigen et al. [25], Recurrent neural network for scene labeling by Pinheiro et al. [26], and restoring dirt clad image using convNet by Eigen et al. [27] is such remarkable example. Training a FCN can be difficult, but has been used for detecting human parts and estimating pose efficiently by Tompson et al. [28].

Different approaches can be taken to get finer segmentation mask exploiting convolutional neural network. One such strategy could be to develop individual system for extracting dense features and detecting zoomed-in edges from images for finer semantic segmentation [29], [30]. A single step process can be, extract semantic feature with convnet and then using superpixels for figuring out the inner layout of the image. Another procedure can be to retrieve superpixels from the given image layout and then extracting features from images one by one [29], [31]. The only drawback of this approach is that the erroneous super pixels may result into fallacious predictions, irrespective how powerful feature extraction took place. Zheng et al. [8], [14] designed a RNN model and used Conditional random field to get more finer features by training an end-to-end network for semantic segmentation. They also proposed a disjointed version of the same model having less accuracy and consuming more memory to prove that an end-to-end network always have an upper hand over two or even three stage effective segmentation retrieval procedure.

Another strategy could be to develop a model and train it using supervised image data and output the segmentation label map for each categories. Retaining the spatial information, one can replace the fully connected layers with convolutional layers in a deep convnet, which was shown by Eigen et al [22]. The most groundbreaking work so far was by Shelhamer and Long et al [4] where the idea was, FCN can be designed to harness features to help classify pixel from the top-most layers, whereas the bottom layers can be used for detecting shapes, contour and edges. With element-wise summation of earlier layers with latter layers they introduced the idea of skip architecture. On the other hand conditional random fields was used to refine semantic segmentation furthermore [8], [14]. CRF was also used by Snively et al. [33] and Chen et al. [9], [34] for refining the existing segmentation mask. Snively et al. conducted recognition for materials and it segmentation, on the other hand Chen et al. developed better ways to obtain finer semantic image segmentation. Though the previous procedures included disjointed CRF for conducting post-processing on the segmented output, the method developed by Torr et al. [8], [14] employed CRF as recurrent neural network and also developed higher order model which is an extension of CRF as RNN. Not only is the convnet is end-to-end but also it converges faster than the previous CRF models and produces finer segmentation mask.

Difference between dilated and vanilla convolution is the extra parameter called holes or dilation that affects the receptive fields of the convolution’s filter. The whole idea of Atrous algorithm, which is based on wavelet decomposition [35] is wholeheartedly based on dilated filter. In [8] Fisher Yu et al. used the term “dilated convolution” instead of “convolution with a dilated filter” to formulate that no dilated filter weren’t built or produced. Convolutional layer was modified instead to make way for a new parameter called dilation to alter the preexisting filter. In [36] Chen et al. made use of dilation to modify the architecture of Shelhamer et al [4] to make it suitable for his task. In contrast, Yu et al. [8] developed a new range of feed forward neural net which exploits dilated convolutions and multi-scale context aggregation but get rid of the preexisting skip architectures.
3 Segmentation Architecture

3.1 Transfer Learning from Classification Net

VGGnet is a famous neural net which won ILSVRC14\cite{1} for image classification. The neural net worked on the principal of using $3 \times 3$ sized filters for feature extraction and concurrently joins each convolutions to make the receptive field bigger. We transferred weights from the VGG 19-layer network, removed the classifier from the network and turned all the fully connected layers to convolutions as done by Shelhamer et al.\cite{4}.

In convolutional neural network all the tensors have three dimensions of size $N \times H \times W$, where $H$ and $W$ are defined as height and width, and $N$ is the color channel or feature output map. At first layer the image is taken as input, where the pixel size is $H \times W$, and the three color channel for RGB is $N$. As described by shelhamer et al.\cite{4} receptive fields is the locations the spatial length of the tensors. If we use the probable value be formulated:

$$r_n \times r_n = (2r_{n-1} + 1) \times (2r_{n-1} + 1) \quad (2)$$

where $r_n$ is the receptive field of the next convolution and $r_{n-1}$ is the receptive field of the previous convolution.

The sixth layer which is the most expensive one comes next. It is a fully connected layer, having a spatial dimension of $4096 \times 4096$ with a filter size $7 \times 7$. The next is also a fully connected layer having a spatial dimension of $4096 \times 1000$ and a filter size of $1 \times 1$. We convert both of this layers to convolutional layers with filter size of $3 \times 3$ and $1 \times 1$ as done by Shelhamer et al.\cite{4}.

3.2 Spatial Information and Receptive Field

The output feature map for each convolutions can be predefined, but the spatial dimension depends on the size of the filter, strides, and padding. FCN architecture tends to keep the spatial dimension of each convolutions same before max-pooling (exception being Fc6 and Fc7 layers). Considering the output channel dimension be $O_{ij}$ and input channel dimension be $I_{ij}$ for any convolution layer, where $i,j$ is the spatial dimension. The equation for output channel dimension will be

$$O_{ij} = \frac{I_{ij} + 2P_{ij} - K_{ij}}{S_{ij}} + 1 \quad (1)$$

Here, $P$ stands for Padding, $K$ is for Kernel or filter size and $S$ is for stride. We choose a filter size of $3 \times 3$, single padding and stride 1 for convolutional layers. This helps us to retain the convolutional structure before pooling to reduce the spatial dimension.

For pooling we use stride of 2 and filter of $2 \times 2$, to lower the spatial length of the tensors. If we use the probable value for filter and stride, in equation 1, then we can see the output becomes half of the size of the input.

The tensors go through first convolution layer to second convolution layer and onward as it is fed forward through the network. In the first two convolution layers we have $3 \times 3$ filters. Therefore the first one has a receptive field of $3 \times 3$ and second one has receptive field of $5 \times 5$. From third to fifth set of convolutional layers we have four convolutions for each of them. So, the receptive field is quite larger than the earlier layers. Notice that receptive fields increases linearly after each convolutions. Let receptive field $r$, filter $f$ and stride be $s$. If the filter and stride values remains the same for concurrent convolutions, an equation to compute the receptive field can be formulated:

$$r_n \times r_n = (2r_{n-1} + 1) \times (2r_{n-1} + 1) \quad (2)$$

where $r_n$ is the receptive field of the next convolution and $r_{n-1}$ is the receptive field of the previous convolution.

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3.3 Decreasing Parameters using Dilation

Fisher et al.\cite{5} combined dilation with vanilla convolution throughout the network and emphasized multi-context aggregation. Whereas, we stick to the original structure of FCN\cite{4} but include dilation only in the sixth convolution, which is the most expensive layer and has the most amount of parameter computation. Similar work was done before in ParseNet, by Liu et al.\cite{13}, but they trained on a reduced version of VGG-16 net. We train on the original VGG-19 classification neural net and only change the filter size and enter dilation as parameter in Fc6 convolution (see Table 1.) while retaining the same number of parameters across all the convolutions. The relation between filter size and dilation can formulated using following equation:

$$K' = K + (K - 1)(d - 1) \quad (3)$$

where $K'$ is the new filter size, $K$ is the given filter size and $d$ is the amount of dilation.

A convolution with dilation 1 is the same as having no dilation. Using equation 3, the filter size of the sixth convolution layer can be changed from $7 \times 7$ to $3 \times 3$ with a dilation size of 3 and filter size of 3. Fisher et al\cite{5} has also defined and equation for calculating the receptive field of a dilated convolution considering the same condition as before:

$$r_{i+1} \times r_{i+1} = (2^{i+2} - 1) \times (2^{i+2} - 1) \quad (4)$$

3.4 Deconvolution with Finer Strides

As upsampling with factor $f$ means using convolution with a fractional input stride of $1/f$ \cite{4}. If $f$ is an integer, we can reverse the forward and backward pass to make the upsampling work by replacing vanilla convolution with transpose convolution. So we use upsampling with finer stride as done by Shelhamer et al.\cite{4} for end-to-end calculation of pixel-wise semantic loss. But the author used strides of 32, 16 and 8, whereas we use a stride of 2 to upsample it in steps. This was done to element-wise summed local features from the bottom layers using skip architectures (discussed in the next section). Figure 1 shows the procedure in details. In 17, transpose convolution layers are called “deconvolution layers”. The deconvolutional layers are used for “bilinear interpolation” as described in 6 rather than learning. It was witnessed by Shelhamer et al.\cite{4} and Torr et al.\cite{8} that upsampling in an end-to-end network is way faster and effective for learning dense prediction.
4 Experiments

4.1 Data-set and Procedure

Pascal VOC Transfer learning was performed by copying weights separately from VGG-19 and VGG-16 classification nets for our two models, Dilated FCN-2s-VGG19 and Dilated FCN-2s-VGG16. We adopt the Back propagation algorithm to train the network end-to-end with forward and backward pass. We used dilation for our most expensive layer, Fc6 as seen in Table 1, which reduced the number of parameters. Resulting into less computation by the machine yet faster inference time. The total time needed was 12 hours for both the networks to get the best mIOU using a single GPU. We used PASCAL VOC 2012 training data counting up to 1464 images. Validation was done on the reduced VOC2012 validation set of 346 images in which we got 58 percent meanIOU.

Table 1. Parameters Comparison

| Architectures | pixel accu. | mean accu. | mean IU | Fw IU |
|---------------|-------------|------------|---------|-------|
| O2P[37]       | -           | -          | 18.1    | -     |
| CMF[38]       | -           | -          | 18.1    | -     |
| FCN-32s       | 65.5        | 49.1       | 36.7    | 50.9  |
| FCN-16s       | 66.9        | 51.3       | 38.4    | 52.3  |
| FCN-8s        | 67.5        | 52.3       | 39.1    | 53.0  |
| CRFsasRNN[8]  | -           | -          | 39.28   | -     |
| HO-CRF[14]    | -           | -          | 41.3    | -     |
| DeepLab-LargeFOV-CRF[39] | - | - | 39.6 | - |
| Ours          | -           | -          | 42.6    | -     |

Semantic Boundaries Dataset Extensive data was used to improve the pixel accuracy and mean-intersection-over-union score of both the models for which the training was done on Semantic Boundaries data-set[20]. The set consists of 8498 training and 2857 validation data. Training was done on both the training and validation data summing up to 11355 images. The reduced set for validation was found by removing the common images in Augmented VOC2012 training set and VOC2012 validation set[15], resulting to 346 images. Our model, Dilated FCN-2s-VGG16 achieves a meanIOU of 64.1 percent and Dilated FCN-2s-VGG19 scores a meanIOU of 64.9 percent. Clearly, the deeper version of the model is more precise for pixel-wise-segmentation. Training was done with learning rate of $10^{-11}$ with 200,000 iterations.

Table 2. Evaluation of Pascal Context data-set

Pascal Context Data-set We train on more sparse data-set like Pascal Context which has 60 classes and pose more chal-
lenging pixel-wise prediction task [40]. The data-set consists of 10103 images. We split the data set into 5105 validation images and rest are used as training set. Our model, scores better mean-IOU of 42.6 percent than the other state-of-the-art models. Moreover, many deeper models with Higher Order CRF as post processing layer scored worse than our model. This clearly indicates that our model is better suited for pixel-wise prediction of sparse data-set. Training was done with learning rate of $10^{-10}$ with 300,000 iterations.

NYUDv2 We train on NYUD version 2, an RGB-D dataset collected with the Microsoft Kinect. It consists of 1,449 RGB-D images, with pixel-wise semantic labels that is divided into 40 semantic classes by Gupta et al. [41]. The data is split into 795 training images and 654 testing images. In, Table 5 the comparison of between fc and our model is given. We train with Dilated FCN-2s VGG19 with three channel RGB images. Then we add depth information and train on a new model upgraded to take four-channel RGB-D input. Though the phenomenon happens does not increase. Long et al. [4] describes this phenomenon happens due to having similar number of parameters or the failure to propagate all the semantic gradients through the net. Following the footstep of Gupta et al. [7], we next train on three-dimensional HHA encoding of depth. The results proves to be more precise and yields better score for our model. Training was done with learning rate of $10^{-10}$ with 150,000 iterations.

### 4.2 Metrics and Evaluation

We use four different metrics to score the pixel accuracy, mean-intersection-over-union, mean accuracy and frequency weighted accuracy. As background pixels numbers in majority, pixel accuracy is not preferable. For semantic segmentation and scene labeling mean-intersection-over union is the most optimum choice for bench-marking.

$$\text{pixel accuracy: } \sum_i N_{ii} / \sum_i \sum_j N_{ij}$$

$$\text{mean accuracy: } (1/\text{num classes}) \sum_i N_{ii} / \sum_i \sum_j N_{ij}$$

$$\text{mean IOU: } (1/\text{num classes}) \sum_i N_{ii} / (\sum_i \sum_j N_{ij} + \sum_i N_{ji} - N_{ii})$$

$$\text{frequency weighted IU: } (\sum_i \sum_j N_{ij})^{-1} \sum_i \sum_j N_{ij} N_{ii} / (\sum_j N_{ij} + \sum_i N_{ji} - N_{ii})$$

where $N_{ij}$ is the number of pixels of class i predicted to belong to class j, $N_{\text{classes}}$ is the number of classes and $\sum_j P_{ij}$ is the total number of pixels of class i. The data was used as it is provided by [15] and [20]. No pre or post processing or augmentation was done to training or validation images to enhance the accuracy of the segmentation output.

In Table 3, Pixel Accuracy, Mean Accuracy, Mean IOU and FW Accuracy comparison between our model and Other FCN architecture. Both of our model outperforms the preexisting FCN structure for the reduced validation set.

| Neural Net                  | MeanIOU |
|-----------------------------|---------|
| FCN-8s [14]                | 62.2    |
| FCN-8s-heavy [4]           | 67.2    |
| DeepLab-CRF [9]            | 66.4    |
| DeepLab-CRF-MSc [19]       | 67.1    |
| VGG19-FCN [42]             | 68.1    |
| Dilated FCN-2s using VGG16 (ours) | 67.6 |
| Dilated FCN-2s using VGG19 (ours) | 69 |

### 4.3 Test Results

The test results as shown on Table 4 indicates our models scoring better than similar FCN architecture in Pascal VOC2012 Segmentation Challenge. We didn’t train on any additional data, neither did we add any graphical model like CRF or MRF [8, 14] to enhance the accuracy further. Reason being it consumes 2× more GPU memory for training. Moreover, our model scores better than FCN model in NYUDv2 sets too (see Table 3). Figure 2 shows the segmentation mask compared to FCN-8s and the ground truth. Also table 5 demonstrates, how less our nets consume memory for training and testing with GPU. As one can see, the reduction in memory usage is more than 20 percent for training with FCN-2s Dilated VGG16.

Both the models where trained and tested with Caffe [43] on Nvidia GTX1060 and GTX1070 separately. The code for this model can be found at: https://github.com/SharifAmit/DilatedFCNSegmentation
Fig. 3. Results after testing on Pascal-Context dataset [40] for 59-classes. The third column of images shows the output of our model which tends to be more accurate. On the second column O2P model’s [38] output which is wrongly predicted in many instances.

Table 6. GPU memory usage comparison

| Model          | GPU Memory Usage Training (MB) | GPU Memory Usage Training + Testing (MB) |
|----------------|--------------------------------|-----------------------------------------|
|Fcn-8s          | 3759                           | 4649                                    |
|Dilated FCN-2s  | 3093                           | 4101                                    |
|VGG16           | 3367                           | 4509                                    |
|Dilated FCN-2s  |                                |                                         |
|VGG19           |                                |                                         |

5 Conclusion

Enhancing accuracy for pixel-wise segmentation requires huge amount of memory and time. Fully convolutional networks can be used to transfer weights from pre-trained net, element-wise summing different layers to improve accuracy and to train end-to-end for entire images with extensive data. Dilation increases the receptive fields while decreasing parameters and inference time. The objective was to create efficient yet deeper architectures for generating accurate output. And the proposed models have efficiently produced accurate pixel-wise segmentation.

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