Semantic Segmentation via Global Convolutional Network and Concatenated Feature Maps

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Abstract: Most of the segmentation CNNs (convolutional neural network) based on the ResNet. Recently, Huang et al. introduced a new classification CNN called DenseNet. Then Jégou et al. used a sequence of building blocks for DenseNet to build their semantic segmentation CNN, called FC-DenseNet, and achieved state-of-the-art results on CamVid dataset. In this paper, we implement the design concept of DenseNet into a ResNet-based semantic segmentation CNN called Global Convolutional Network (GCN) and build our own network by switching every identity mapping operation of the decoder network in GCN to a concatenation operation. Our network uses less computational resources than FC-DenseNet to obtain a mean IoU score of 69.34% on CamVid dataset, and surpass the 66.9% obtained in the paper of FC-DenseNet.

1 INTRODUCTION

Semantic segmentation is a challenging computer vision problem of assigning semantic labels (e.g., car, person, etc.) to each pixel in the given image. It is a crucial step towards scene understanding. It improves image classification to pixel-wise level and could further be enhanced to instance segmentation which distinguishes different instances from the same semantic class. A good semantic segmentation technique could be useful in a lot of applications such as self-driving or other environmental monitoring products.

In recent years, convolutional neural network (CNN) has driven significant progression in image classification. Networks like (Krizhevsky et al., 2012; Simonyan et al., 2014; Szegedy et al., 2015; He et al., 2016; Huang et al., 2017) broke the records of many challenging benchmarks (Deng et al., 2009; Lin et al., 2014; Krizhevsky et al., 2009) one after another. Fully convolutional network (FCN) (Long et al., 2015) introduced the concept of fully convolution for replacing fully connected layers in the last part of the classification networks (Krizhevsky et al., 2012; Simonyan et al., 2014; Szegedy et al., 2015). It enables these networks to make semantic segmentation prediction under down-sampled resolution. For up-sampling the prediction back to original resolution, they took these classification networks as a feature encoder network and used the skip connection to restore the spatial information from the feature maps in the middle layers of the encoder network. This skip architecture design achieved a state-of-the-art result and proved that the pre-trained classification networks could be extended to semantic segmentation networks.

After FCN, more and more semantic segmentation methods (Lin et al., 2017; Peng et al., 2017; Jégou et al., 2017) used this skip architecture to design their own decoder networks for up-sampling the feature maps of classification networks. One of the methods, (Peng et al., 2015), suggested that there still have some differences between the principles of doing classification and segmentation. For example, classification should be invariant to various image transformations, but segmentation has to be sensitive to this spatial information. They believed that network not only needs to use fully convolution and remove global pooling to retain the localization information but also has to use large convolution kernels to enhance the capability to handle different transformations. Following this principle, they proposed a decoder network called Global Convolutional Network (GCN) and achieved state-of-the-art results on Cityscapes (Cordts et al., 2016) and Pascal-VOC

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2012 (Everingham et al., 2010) datasets by using ResNet (He et al., 2016) as thier encoder network.

In 2017, Huang et al. introduced a new classification CNN called DenseNet where the input of each building block is an iterative concatenation of previous feature maps. It is similar to ResNet which using summation through identity mapping, but according to (Jégou et al., 2017), this small modification brings lots of positive effects to the network, including: (1) parameter efficiency, (2) implicit deep supervision, and (3) feature reusing. They used the building block of DenseNet to build both the encoder network and the decoder network with skip connections and named their network as FC-DenseNet, where FC stands for fully convolution. It used significantly fewer parameters to achieve state-of-the-art results on CamVid (Brostow et al., 2008) dataset without pre-training on any dataset.

Despite the success of FC-DenseNet, we still agree with Peng et al. that there exist additional requirements on architecture for doing segmentation task. We should design the decoder network based on the principles of both DenseNet and GCN. In this paper, we focus on utilizing the concatenation operation to every blocks in the decoder architecture of GCN. Therefore, we can take the advantage of DenseNet and keep the same segmentation process of GCN at the same time. We take reference to FC-DenseNet and name our network as GC-DenseNet.

2 RELATED WORK

Since the size of an object in an image could be various, semantic segmentation CNNs require various field-of-views to recognize the objects. An intuitive way is using multi-input to generate multi-scale features. For example, (Chen et al., 2016) used an attention model to decide which scale features are more useful at each location. Another way is using multi-path architecture to generate multi-scale features. DeepLab (Chen et al., 2018) introduced an “atrous spatial pyramid pooling” (ASPP) architecture that use dilation convolutions with different rates to create multi-scale features. As comparison, PSPNet (Zhao et al., 2017) used a similar architecture simply through different sizes of pooling.

Another kind of methods is FCN-based networks such as FC-DenseNet (Jégou et al., 2017) and GCN (Peng et al., 2017), which reused the feature maps in the encoder network to obtain multi-scale field-of-views. FC-DenseNet tried to implement dense block (Huang et al., 2017) in their decoder network. Unlike other FCN-based methods using pre-trained classification network, they re-built the encoder with five dense blocks according to their own combination. Finally, they built the decoder symmetrical to the encoder. Since the number of feature map channels increase each time through a building block, it will be computationally expensive for the decoder network. They did not transfer previous feature maps to the next dense block during up-sampling. However, we think it violates the principle of DenseNet and causes their network could not improve further.

GCN is the network we reference the most. It took pre-trained ResNet as the encoder network and used global convolutional networks to extract classification features from the encoder network. It is constructed by 2 pairs of $1 \times k$ and $k \times 1$ convolution layers with different orders where k is an editable kernel size. To further refine the prediction around object boundary, they added boundary refinement blocks after each GCN block and up-sampling layer. They set the output channels of every blocks in the decoder network to the number of semantic classes. Each GCN block would learn to make a segmentation prediction under different field-of-views.

3 METHOD

To present our method, we will introduce the overview of our semantic segmentation network in section 3.1. Then, in section 3.2, we will explain the architecture details of each block in our network.

3.1 Overview

Since our network is based on the architecture of GCN (Peng et al., 2017), we take architecture figure in their paper as reference to draw the overview of our network in Figure 1. In Figure 1(a), we show the overview of our network architecture. The leftmost column is a DenseNet (Huang et al., 2017) without the classification layer. It is our encoder network. The rest of the blocks construct our decoder network. Each output feature map of a “dense block” (DB) is transferred through a “global convolution” (GC) block and a “boundary refinement” (BR) block. Then the feature map with lower resolution is up-sampled by a “transposed convolution layer” (TC) and concatenated (Concat.) with the higher resolution one. After a sequence of up-sampling, the last feature map is passed to the final BR block.

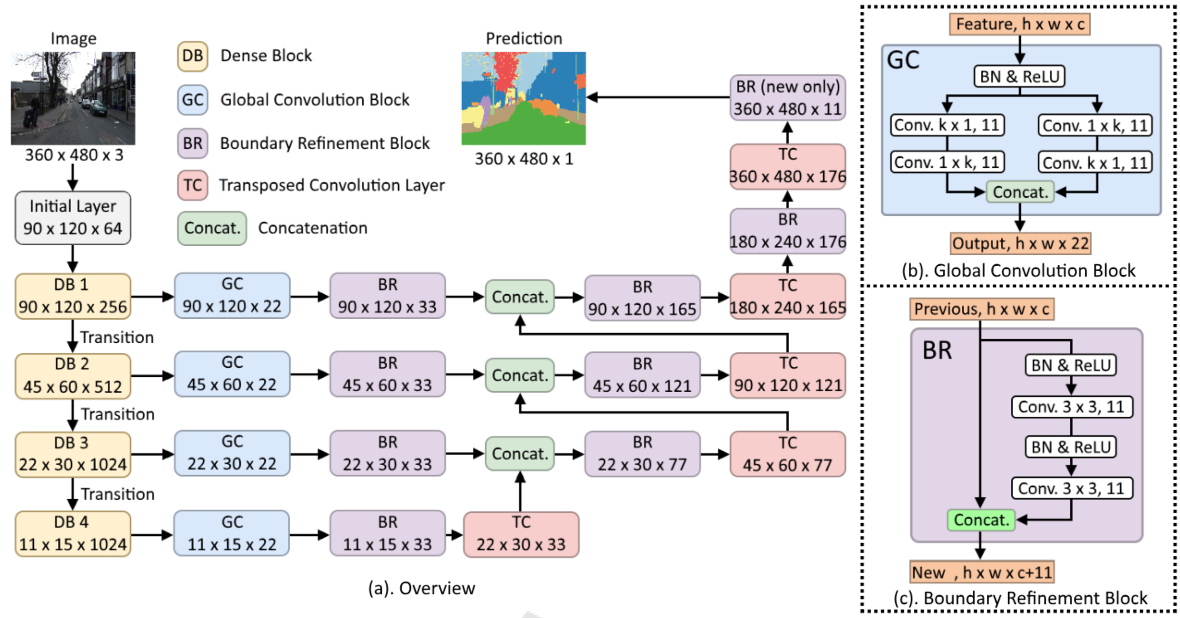


Figure 1: Architecture of our network. (a) Overview of the whole network. (b) Global convolution block architecture. (c) Boundary refinement block architecture.

It abandons the previous feature maps and generates a score map with 11 channels corresponding to 11 semantic classes in the CamVid dataset (Brostow et al., 2008). Finally, the prediction of each pixel label is determined to be the class with the highest score.

3.2 Architecture Details

Unlike ResNet down-sampling the feature maps at the first convolution layer in each ResNet block, DenseNet implements it at the transition layers. We replace the ResNet in GCN with DenseNet and skip connect the output feature maps of each dense block to our global convolution block before transition layers.

Our main modification of the decoder network in GCN is switching every identity mapping operation to a concatenation operation. To make each block act more like a building block for DenseNet, we add the batch normalization (Ioffe et al., 2015) and ReLU (Nair et al., 2010) before of global convolution blocks and the convolution layers in boundary refinement blocks. Since there always has a batch normalization after the convolution layer, we remove the bias operation in every convolution layers.

As for up-sampling layer, we use transposed convolution (Noh et al., 2010) with 3×3 kernel and stride 2. Due to concatenation operations, the number of feature map channel will not remain the same like GCN does. Thus we remove the concatenation in the last boundary refinement block. It only outputs the new feature map with channel equals to the number of semantic classes.

4 EXPERIMENTAL RESULTS

In this section, we will first introduce the training details of our network in section 4.1. Then, we conduct several experiments with different network settings in section 4.2 to find the best result of our network. Finally, we compare our best setting network with other networks in section 4.3.

We use "mean intersection of union" (mIoU) to measure the performance. The mIoU of every semantic classes "$Class$" are computed by:

$$mIoU = \frac{1}{\|Class\|}\sum_{c\in Class}\frac{TP_c}{TP_c+FP_c+FN_c}, \qquad (1)$$

where TP_c, FP_c, and FN_c denotes the number of pixels belong to "true positive", "false positive", and "false negative" of the prediction on class "c". Therefore, the score value will be always between 0%~100%, and the higher is the better.

4.1 Training Details

We use PyTorch (Paszke et al., 2017) to implement our network models. We evaluate our network performance on CamVid (Brostow et al., 2008) dataset. It is a 360×480 urban scene video frame dataset which consists of 367 frames for training, 101 frames for validation, and 233 frames for testing. Each frame is fully labelled with 11 semantic classes and a void class.

We add dropout layers with 0.2 dropping rate after each block in the decoder network and the building blocks in the DenseNet. All models are trained on data augmented with random horizontal flips and normalization on RGB channels.

We initialize our models using HeUniform (He et al., 2015) and train them using Adam (Kingma et al., 2014) with 175 epochs and a batch size of 4. We set the initial learning rate of 10^{-4} and multiply it by 0.4 at epoch 125 and 150. Finally, we regularize our model with a weight decay of 10^{-4}. All of our network trainings run on a Nvidia GTX 1080 GPU with 8GB memory.

4.2 Finding the Best Setting

Since DenseNet (Huang et al., 2017) has different depth version pre-trained on ImageNet (Deng et al., 2009), we want to find the best suit version for our network. We use the same size of global convolution kernel (k=7) to train our network with different DenseNet depth in Table 1. The results show that DesneNet-121 is the best choice for our network on CamVid dataset. We believe it is because that CamVid is a dataset much smaller than ImageNet comparing to the number of classes and data. It does not need that many parameters to solve the problem.

Then we need to find the best kernel size of global convolution kernel. Based on the above experiment, we use DesneNet-121 and transposed convolution to build our network with different global convolution kernel size k in Table 2. In contrast to Peng et al. finding k =15 is the best size on Pascal-VOC 2012 (Everingham et al., 2010), we get the best result at k = 7 on CamVid instead. We think the reason is that CamVid dataset does not contain any object with the full image size like Pascal-VOC 2012.

Table 1: Comparison of DenseNet depth on CamVid testing dataset.

	Depth = 121	Depth = 169	Depth = 201
mIoU (%)	**69.34**	69.03	69.14

Table 2: Comparison of global convolution kernel size on CamVid testing dataset.

	k = 3	k = 7	k = 11	k = 15
mIoU (%)	68.87	**69.34**	68.61	67.77

Table 3: Comparison of GCN and our network.

	GCN-ResNet	GCN- DenseNet	ours
mIoU (%)	64.15	64.69	**69.34**

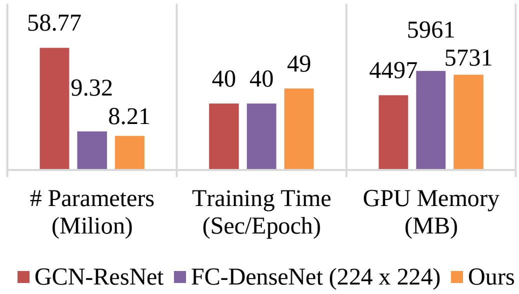


Figure 2: Computational efficiency for GCN-ResNet, FC-DenseNet, and ours.

Hence we do not need a kernel with the full size of the final output feature map of encoder network.

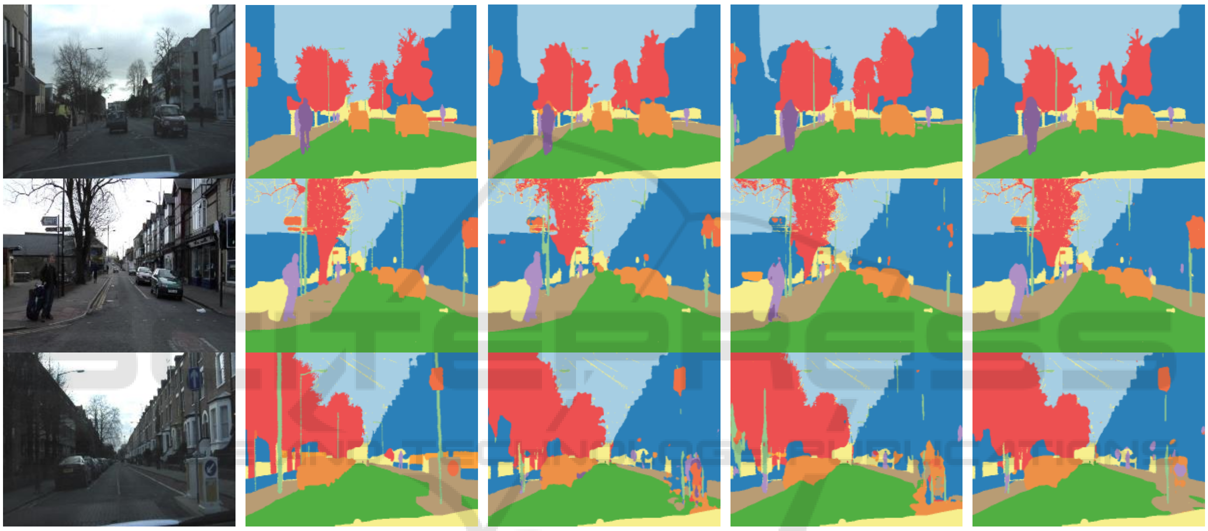
4.3 Comparing to Other Networks

Since (Peng et al., 2017) only evaluate GCN on Pascal-VOC 2012 (Everingham et al., 2010) and Cityscapes (Cordts, 2016), we have to implement the network and evaluate it on CamVid (Brostow et al., 2008) by ourselves. Additionally, we hope to distinguish our contribution of modifying the decoder network from simply replacing the ResNet with the DenseNet. Therefore, we also build a DenseNet version of GCN, which only switch the encoder network without doing any modification on the decoder network. We denote this model as GCN-DenseNet and compare these two versions of GCN to our network in Table 3. All the networks uses 7×7 global convolution kernels. The results show that DenseNet really is better than ResNet in semantic segmentation task. However, the difference is not that obvious. On the contrary, our modification of the decoder network does contribute most of the improvement because we use concatenation to provide more flexibility for the feature combination.

Since DenseNet use much fewer parameters than ResNet, we will not just compare the computational efficiency to GCN-ResNet. We also compare our network with FC-DenseNet. In Figure 2, we compare the number of training parameters, training time of each epoch, and the consumption of GPU memory on GCN-ResNet, FC-DenseNet, and our network. All the networks are trained with batch size of 4. Unlike GCN-ResNet, ours is trained with full size images, while FC-DenseNet is only trained with

Table 4: Comparison of our and other networks in each class IoU (%).

Model	# parameters (M)	Sky	Building	Pole	Road	Sidewalk	Tree	Sign	Fence	Car	Pedestrian	Cyclist	mIoU (%)	Pixel Accuracy (%)
FC-DenseNet	9.32	90.92	81.93	35.34	**95.22**	83.60	75.56	43.32	36.93	80.51	**57.20**	45.15	65.97	91.27
GCN-ResNet	58.77	91.56	82.70	26.45	93.76	78.95	76.11	40.08	36.67	82.79	50.15	46.39	64.15	90.96
GCN-DenseNet	**7.42**	91.50	83.61	30.46	94.93	**84.04**	76.09	37.66	39.98	78.12	51.36	43.79	64.69	91.53
GC-DenseNet	8.21	**92.32**	**84.71**	**35.91**	94.69	82.15	**77.06**	**46.69**	**46.22**	**84.86**	56.15	**61.94**	**69.34**	**92.14**



(a) Input (b) Ground Truth (c) GCN-ResNet (d) FC-DenseNet (e) Our method

Figure 3: Comparison of our method and other methods.

224×224 random cropped patches.

Although GCN-ResNet uses much more parameters, it takes less GPU memory and trains faster than our network, because FC-DenseNet and our network use more channels of the feature maps in the decoder network. As for FC-DenseNet, it uses slightly more parameters and memory than ours. The only downside of our network is it trains slower than other networks, because it has more channels in the decoded feature maps with higher resolution. In Figure 3, we show our results is better than GCN-ResNet and) FC-DenseNet in detail such as the sign pole in the image.

In Table 3, we show each semantic class IoU separately and mIoU of each network. We also compute the pixel accuracy to see how many pixels are predicted correctly. Despite GCN-DenseNet is our experimental network, our GC-DenseNet use the least number of parameters and achieve the highest mIoU score. Our network brings improvement on almost every classes, especially those classes with low mIoU score.

5 CONCLUSION

In this paper, we propose a semantic segmentation CNN that modifies the GCN-ResNet (Peng et al., 2017) with concatenation architecture introduced in DenseNet. Although our network takes more GPU memory comparing to GCN-ResNet, it uses fewer parameters and achieves the mIoU score higher than GCN-ResNet and FC-DenseNet in CamVid dataset.

In contrast to DenseNet-264 obtaining a classification accuracy close to the ResNet-152, we simply use DenseNet-121 in GCN-DenseNet to achieve the mIoU score better than GCN-ResNet, which use ResNet-152 as the encoder network. It shows that concatenation architecture is more suitable than identity mapping architecture for semantic segmentation.

REFERENCES

Krizhevsky, A., Sutskever, I., Hinton, G. E., 2012. ImageNet classification with deep convolutional neural networks. In *Conference on Neural Information Processing Systems*, pp. 1097-1105.

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

Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., Rabinovich, A., 2015. Going deeper with convolutions. In *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1-9.

He, K., Zhang, X., Ren, S., Sun, J., 2016. Deep residual learning for image recognition. In *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 770-778.

Huang, G., Liu, Z., Maaten, L. van der, Weinberger, K. Q., 2017. Densely connected convolutional networks. In *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2261-2269.

Deng, J., Dong, W., Socher, R., Li, L. J., Li, K., Li, F. F., 2009. ImageNet: A large-scale hierarchical image database. In *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 248-255.

Lin, T. Y., Maire, M., Belongie, S., Bourdev, L., Girshick, R., Hays, J., Perona, P., Ramanan, D., Zitnick, C. L., Dollár, P., 2014. Microsoft COCO: Common objects in context. In *European Conference on Computer Vision*, pp. 740-755.

Krizhevsky, A., Hinton, G. E., 2009. Learning multiple layers of features from tiny images. In *Tech Report, University of Toronto*.

Long, J., Shelhamer, E., Darrell, T., 2015. Fully convolutional networks for semantic segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3431-3440.

Lin, G, Milan, A., Shen, C., Reid, I., 2017. RefineNet: Multi-path refinement networks for high-resolution semantic segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 5168-5177.

Peng, C., Zhang, X., Yu, G., Luo, G., Sun, J., 2017. Large kernel matters -- Improve semantic segmentation by global convolutional network. In *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1743-1751.

Jégou, S., Drozdzal, M., Vazquez, D., Romero, A., Bengio, Y., 2017. The one hundred layers tiramisu: Fully convolutional DenseNets for semantic segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1175-1183.

Everingham, M., Gool, L. V., Williams, C. K. I., Winn, J., Zisserman, A., 2010. The PASCAL visual object classes (VOC) challenge. In *International journal of computer vision*, pp. 303-338.

Cordts, M., Omran, M., Ramos, S., Rehfeld, T., Enzweiler, M., Benenson, R., Franke, U., Roth, S., Schiele, B., 2016. The cityscapes dataset for semantic urban scene understanding. In *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3213-3223.

Brostow, G. J., Shotton, J., Fauqueur, J., Cipolla, R., 2008. Segmentation and recognition using structure from motion point clouds. In *European Conference on Computer Vision*, pp. 44-57.

Chen, L. C., Yang, Y., Wang, J., Xu, W., Yuille, A. L., 2016. Attention to scale: Scale-aware semantic image segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3640-3649.

Chen, L. C., Papandreou, G., Kokkinos, I., Murphy, K., Yuille, A. L., 2018. DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. In *IEEE Transactions on Pattern Analysis and Machine Intelligence*, pp. 834-848.

Zhao, H., Shi, J., Qi, X., Wang, X., Jia, J., 2017. Pyramid scene parsing network. In *IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2881-2891.

Ioffe, S., Szegedy, C., 2015. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *International Conference on Machine Learning*, pp. 448-456.

Nair, V., Hinton, G. E., 2010. Rectified linear units improve restricted boltzmann machines. In *International Conference on Machine Learning*, pp. 807-814.

Noh, H., Hong, S., Han, B., 2015. Learning deconvolution network for semantic segmentation. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1520-1528.

Paszke, A., Gross, S., Chintala, S., Chanan, G., Yang, E., DeVito, Z., Lin, Z., Desmaison, A., Antiga, L., Lerer, A., 2017. Automatic differentiation in PyTorch.

He, K., Zhang, X., Ren, S., Sun, J., 2015. Delving deep into rectifiers: Surpassing human-level performance on ImageNet classification. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1026-1034.

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