1 Introduction

Semantic segmentation is one of the most fine-grained and challenging computer vision tasks. The goal is to label every pixel in the image with one of the several predetermined categories. Given enough manually labelled training data, current deep learning methods achieve impressive performance [3]. However, the pixel-level annotations are laborious and expensive to collect, so weakly-supervised semantic segmentation is receiving growing attention and will have a significant impact on this area.

The existing weakly supervised semantic segmentation methods are mainly based on various annotations including bounding boxes, user scribbles, web images, saliency masks and image-level labels. To clarify the problem setting and for a fair comparison, we consider the annotation needed for the overall segmentation system including the supervision of the intermediate modules. A segmentation network may require both image-level class labels and super-pixels as supervision. If the super-pixel is generated based on prior knowledge of the image-level properties, we consider this method as an image-level weak supervision method. However, if the super-pixel generator is trained with annotations other than image labels, these will be counted as additional supervision required by the system. Similarly, saliency, i.e., the foreground/background mask, is very helpful for segmentation, and we found that in the PASCAL VOC 2012 augmented dataset [6], [5], [10], there are 12030 images in total, and 7673 of them contain only one class, i.e., for over 63% of the cases the saliency is equivalent to the segmentation mask. For a fair comparison, the annotation needed to train the saliency detector should be counted in the supervision of the overall segmentation system.

Since image level annotation, i.e., class labels, are abundant and relatively cheap to collect, we build a segmentation system that only requires image-level class labels during training. Our work is mainly inspired by SEC [16], where the class-specific activation maps are extracted from a well-trained classifier through class activation maps (CAM) [36]. The active regions are served as high confidence cues to train a segmentation network. The main contribution of SEC [16] is to define the loss function that contains three terms, i.e., the seeding loss to impose the activation in the discriminative region, which is not necessary to be the whole object. We refine the activation cues from a well-trained classifier by snapping it to the super-pixels in the image. We also train another classifier using gray images as the expansion loss which penalizes the classification error. Among the three loss terms, the seeding loss plays a crucial role, and our idea is to improve these segmentation cues. We also modify the training and testing procedure.

It is known that the activation in the hidden layer feature maps of a well-trained classifier localizes the region of interest, but it has the following limitations for the segmentation tasks: 1) it is too coarse, and 2) it only highlights the discriminative region, which is not necessary to be the whole object. We refine the activation cues from a well-trained classifier by snapping it to the super-pixels in the image. We also train another classifier using gray images to extract cues that capture more structural information, then fuse the cues from the two classifiers to train the segmentation network. We omit the classification loss in the original SEC since we found that it makes the mask over discriminative and decreases the performance if the weight of this loss term is not carefully chosen. After generating cues, we preserve the classifier, and not only use its weights...
to initialize the segmentation network, but also use its prediction in the testing phase to amend the segmentation mask by suppressing the nonexistent classes.

To summarise, we contribute a weakly-supervised semantic segmentation system that only requires image labels for training. The novel modules of the system are listed as follows:

1) It refines the class-specific activation mask from a classifier by snapping it to the super-pixels.
2) It extracts more structural information by training an additional classifier with pure gray images.
3) The CRF process in the testing phase is regulated by the classifier.

Experimental results show that our proposed system outperforms the baseline by a large margin, and its performance is comparable with the state-of-the-art.

2 RELATED WORK

Weakly supervised semantic segmentation has been extensively studied to relieve the data deficiency problem. According to the types of annotation required by the overall system, existing weakly-supervised methods are based on various problem settings.

For example, user scibble [29], [29] and abundant web images [24], [25] are considered to regulate the training process or enrich the training data. Assisted by bounding box, [4] iterates between automatically generating region proposals and training convolutional networks alternatively. With pre-trained object detector to reduce the accumulated error, Qi et al. [21] propose a training algorithm that progressively improves segmentation performance with augmented feedback in iterations. Saleh et al. [23] extracts the foreground/background mask from a classifier, then obtains multi-class masks by fusing them with information extracted from a weakly-supervised localization network. Isola et al. [14] considers crisp boundary detection as higher-order terms for CRF refinement.

A large group of works incorporate supervised pre-trained saliency detector to first generate good foreground/background masks, then use them to obtain class-specific segmentation masks [20], [2], [32], [32], [9], [13], [34], [31], [7], [28]. As mentioned in the previous section, in the popular semantic segmentation dataset PASCAL VOC 2012 [6], [30], over 63% of the images contain one class, where the saliency is equivalent to the semantic segmentation mask, and in all the cases, precise saliency can at least offer precise background mask. With the help of a well-trained saliency detector, these methods significantly outperform those trained with image labels only. However, most of the saliency detectors are trained in a fully-supervised manner, and the pixel-wise foreground annotations are still costly to produce.

The challenge of obtaining the semantic segmentation mask with only image label supervision is addressed in different ways. A multi-step pipeline [26], [27] is proposed to extract class specific maps from a classifier by 1) modifying the activation map calculation, 2) subtracting the activation maps of other classes from that of the target class, 3) aggregating multiple-scale, and 4) augmenting training data for only good cases. Kim et al. [15] tries to get more complete activation masks through two phases training. In the second phase, the highly discriminative activations from the first training phase are suppressed, forcing the network to discover the next most important parts. However, it is not clear why suppressing the activation of one part leads to the discovering of another, since there is no clear competition between them. In other words, as long as activating more parts helps to reduce the loss, the network should do so, and including more parts can be achieved simply by lowering the threshold. Roy et al. [22] specifies a deep architecture that fuses the cues from three distinct computation processes via a conditional random field as a recurrent network aiming at generating a smooth and boundary-preserving segmentation. Kwak et al. [18] proposes Superpixel Pooling Network (SPN), which utilizes superpixel segmentation of input images as a pooling layout to reflect the low-level image structure for learning and inferring semantic segmentation. AffinityNet [11] predicts semantic affinity between a pair of adjacent image coordinates. The propagation of the activation from local discriminative parts to the entire object is then realized by one random walk with the affinities predicted by AffinityNet. Kolesnikov et al. [16] uses cues from a well-trained classifier as a partial segmentation mask for training, and defines the loss function that contains three terms, i.e., the seeding loss to impose the activation in the cue region, the constrain-to-boundary loss to encourage the consistency of the segmentation masks before and after applying CRF, and the expansion loss, which penalizes the classification error.

Our system adopts the main procedure of [16], and modifies it by three ways: 1) snapping the cues to the super-pixels in the image, 2) fusing the cues of a color image trained classifier and that of a gray image trained classifier to cover more parts, and 3) using prediction of the classifier to suppress non-exist classes during testing. Unlike [18], [1], our super-pixels are calculated based on the properties of natural images, and no training is involved in predicting the affinities between pixels.

3 PROPOSED METHOD

3.1 Problem formulation

Let us model each pixel label as a random variable $X_i$ associated with pixel $i$ in image $I$. $X_i$ can take any one label from a pre-defined set $L = \{l_1, l_2, \ldots, l_K\}$. The segmentation goal is to obtain labels for all the random variables $X = \{X_1, X_2, \ldots, X_N\}$ given observation $I$, where $N$ is the total number of pixels in the image. Our segmentation network $F_{seg}()$ is a fully convolutional neural network (FCN) whose outputs $F_{seg}(I) = \{f_1, f_2, \ldots, f_K\}$ are $K$ channel maps. For a well-trained segmentation network, the value at location $p_i$ in the $j_{th}$ output map represents the probability that pixel $i$ belongs to class $j$, i.e., $f_j(p_i) = p(X_i = l_j | I)$. CRF [19], [17] is applied to $F_{seg}(I)$ for further refinement. Its unary potential is given by

$$\psi_u(X_i = l_j) = -\log f_j(p_i),$$

1. resize to that of $I$ if needed.
and pairwise potential is the commonly used
\[
\psi_p(i, j) = \omega_1 \exp\left( -\frac{||p_i - p_j||^2}{2\sigma^2} - \frac{||I_i - I_j||^2}{2\sigma^2} \right) \\
+ \omega_2 \exp\left( -\frac{||p_i - p_j||^2}{2\sigma^2} \right),
\]
where \(p_i\) and \(I_i\) are the location and color of pixel \(i\).

### 3.2 Proposed system overview

There are four major steps in our proposed system: 1) classifiers training, 2) cue generation, 3) segmentation network training, and 4) testing. The first two steps are illustrated in Figure 1 and the last two steps are illustrated in Figure 2.

We first train two classifiers using color images and gray images respectively with multi-label cross entropy loss, then extract a set of cues from each classifier and fuse them. A set of cues are binary class-specific activation maps that have the same shape as \(F_{seg}(I)\). They indicate the confident elements in the coarse segmentation results, and serve as an incomplete pseudo annotation to train the segmentation network. Following SEC [16], suppose \(C\) is a set of cues, then the seeding loss \(L_s\) has the following form:

\[
L_s = -\frac{1}{|C|} \sum_{i \in \{C(i) = 1\}} \log F_{seg}(I)(i),
\]

where \(|C|\) is the total number of elements with value 1 in \(C\).

The other loss term we use is the constrain-to-boundary loss [16]. Let \(L(I, F_{seg}(I))\) denote the result of applying CRF refinement on \(F_{seg}(I)\), the constrain-to-boundary loss \(L_c\) is the KL-divergence between \(F_{seg}(I)\) and \(Q(I, F_{seg}(I))\):

\[
L_c = \frac{1}{n} \sum_i Q(I, F_{seg}(I))(i) \log \frac{Q(I, F_{seg}(I))(i)}{F_{seg}(I)(i)},
\]

where \(n\) is the total number of elements in \(F_{seg}(I)\).

As shown in Figure 2 in our system, the full loss used to train \(F_{seg}(\cdot)\) is: \(L = L_s + L_c\). In the testing phase, the prediction from the color image trained classifier is used to amend the result of the segmentation network \(F_{seg}(I)\) before CRF refinement. The key parts of our proposed system are detailed in the following two subsections.

### 3.3 Cue Generation

In our system, foreground class-specific activation maps are obtained through CAM [36]. We adopt the modification in [26], [27], i.e. subtracting the activation maps of other classes from that of the target class to obtain clearer separated objects. The binary cues are the pixels above 30% of the maximum value in an activation map. To generate the background map, we first summarize all the feature maps of the top two convolutional layers from the classifier, then normalize the result to \([0, 1]\). The pixels with their value smaller than 0.2 are used as background cues. In Figure 5 (better viewed in color), some sample images are shown in the first column, each with its ground truth segmentation shown in the second column. The fourth column contains the binary cues directly obtained from a classifier. It can be seen that they are coarse, and a large portion of each image is uncovered. We propose to refine the cues by snapping them to the super-pixels calculated through [8]. An important characteristic of this method is its ability to preserve detail in low-variability image regions while ignoring detail in high-variability regions. The super-pixels calculated by [8] are shown in the third column in Figure 3. We average the cue value in each super-pixel, and binarize the result with a threshold that equals to 0.3 times the maximum value in the mask. The snapped cues are shown in the fifth column. Compared with the raw cues, the snapped cues are improved in two ways: 1) the boundaries are better aligned with those of the objects, and 2) both foreground and background cues are spread to cover more complete regions.

As shown in Figure 1, another countermeasure we take against the incompleteness of the generated cues is to fuse two sets of cues extracted from a color image trained classifier and a gray image trained classifier. This procedure is motivated by our two observations: 1) we found that in the PASCAL VOC 2012 dataset [6], [30] some images suffer severe color distortion due to overexposure and extreme light condition, and 2) the class-specific activation maps from a gray image trained classifier can cover more parts that are discriminative in structure but not in color. For example, a color image trained classifier usually ignores the legs of a person since his/her pants can have any color and this high variance information seems not to help the classification task. However, in gray images all people’s legs have a similar structure then the network can find these regions are helpful to distinguish people from other classes. The way we merge two sets of binary cues is simply by applying logical OR. The last column in Figure 3 shows the merged cues, which are better than both cues from a color image trained classifier [36] and that from a gray image trained classifier [56].

### 3.4 Decouple classification from segmentation

As shown in the top of Figure 2 after the cues are generated, they are used to train the segmentation network. The loss function in SEC [16] contains three terms, i.e. the seeding loss imposes the activation in the cue region; the constrain-to-boundary loss, which is the KL-divergence between the outputs of the segmentation network and that of the CRF [19], [17]; and the expansion loss, which is the multi-label classification error. In our system, we reserve the seeding loss and constrain-to-boundary loss, but omit the classification error. The reason for this decouple is that we observe the conflict between the needs of classification and segmentation. For example, some patterns are shared by multiple classes, e.g., the body fur of cats and dogs, and the wheels of cars and buses, while a classification loss that drives the network to highlight the region that can uniquely identify a class will make the activation maps over discriminative and incomplete for segmentation purpose.

### 3.5 Prediction amend testing

We use our previously color image trained classifier in three ways: 1) to generate cues, 2) to initialize the segmentation network, and 3) to amend the result in testing, as shown in the bottom half of Figure 2. Since the cues used to train the segmentation network are incomplete, i.e., only some
Fig. 1: Training classifier and cue generation. The dashed arrows indicate the processes without backward propagation.

Fig. 2: Training and testing the segmentation network. The dashed arrows indicate the processes without backward propagation.

pixel locations are included, the segmentation network can produce non-exist classes. The damage of a few wrongly activated pixels can be amplified by CRF, which propagates the unary by location closeness and color similarity. This problem can be relieved by using the prediction of a classifier to suppress the non-exist classes. During the testing phase in our system, at each pixel location, the maximum scores among the predicted classes are used as the ceiling value \( c_i = \max_{j \in S_{\text{pred}}} f_j(p_i) \), and the scores in predicted non-exist classes are suppressed to below this ceiling by a small margin \( 1e^{-4} \). The effectiveness of this method is shown in the next section.

4 Experiments

In this section we validate our proposed system experimentally.

2. Notice that FCN-C, FCN-G and FCN-S are actually the same fully-convolutional structures. FCN-C and FCN-G are trained from color and gray images respectively. FCN-S is trained for the final segmentation and initialized from FCN-C. It is the same for the 1x1conv layer which is a 2D convolutional layer with kernel size of 1 x 1.
Fig. 3: Illustration of proposed cue generation method. Each row contains one example and from left to right shows: (a) original image, (b) ground truth segmentation mask, (c) the calculated super-pixels, (d) the cues extracted from a color image trained classifier (CC), (e) snapping CC to the super-pixels, (f) the cues extracted from a gray image trained classifier (GC), (g) snapping GC to the super-pixels, and (h) merging cues from snapped CC and snapped GC.

4.1 Dataset

Our proposed method is evaluated on the PASCAL VOC 2012 image segmentation benchmark [6], [30], which has 20 foreground classes and 1 background class. The dataset contains 1464 images for training, 1449 images for validation and 1456 images for testing. Following the common practice, we use the augmented training set, i.e., trainaug set, which has 10,582 images, from [10]. Both evaluation and testing
results are reported and intermediate results are shown on the evaluation set only since the ground truth segmentation masks for the testing set are not publicly available. We use the standard PASCAL VOC 2012 segmentation metric mean intersection-over-union (mIoU).

### 4.2 System evaluation

The effectiveness of our proposed system can be seen from Table 1. We test our method on two networks, and the detailed network structures can be found in Res38 [35], I and Res50 [11]. As described in section 3.1, the segmentation results are obtained from the CNN masks, i.e. $F_{seg}(I)$, and are refined by CRF [19], [17]. CAM means the $F_{seg}(I)$ is obtained from a classifier through CAM [36]. Raw cue, snapped cue and merged cue means the $F_{seg}(I)$ are the outputs of a segmentation network trained by raw cues, super-pixel snapped raw cues and merged cues respectively. With prediction means the non-existing classes in $F_{seg}(I)$ are suppressed before CRF according to the prediction of a classifier, as described in sub-section 3.5 and with class labels means using ground truth class labels, which shows the upper-bound performance gain of this process. Acc and Rec means the accuracy and recall of these networks when they are trained as classifiers. It can be seen that merged cue outperforms snapped cue, which outperforms both raw cue and CAM. This means our proposed cue generation method effectively refines the raw cues and makes them more complete. Using the predictions from a classifier to amend $F_{seg}(I)$ steadily improve the mIoU.

### 4.3 Cue evaluation

One of our main contributions is to modify the raw cues extracted from the classifiers by 1) snapping the cues to super-pixels, and 2) merging the cues from a color image trained classifier and a gray image trained classifier. In this sub-section, we directly evaluate the cues of training data by mIoU. Since the cues are partial annotations, the unknown pixels in the cues are treated as background. Both the mIoU of all the classes and that of the foreground classes are shown in Table 2. It can be seen that our proposed method indeed improve the quality of the cues.

### 4.4 Comparison with other methods

In this sub-section the proposed method is compared with the latest works under the problem setting that only image labels are used in training, without other annotations through the whole system. The results on PASCAL VOC 2012 image segmentation benchmark [6], [8] validation data and test data are shown in Table 3 and Table 4 respectively. It can be seen that the performance of our proposed method is comparable with that of the state-of-the-art. The only method outperforming us is [11], which involve training an extra AffinityNet and random walk process.

### 5 Conclusion

In this paper, we propose a novel weakly-supervised semantic segmentation method using image-level labels only. The cues extracted from the well-trained classifiers are used as incomplete annotations to train a segmentation network. We propose to modify the raw cues by 1) snapping them to the super-pixels; 2) merging two sets of cues from a color image trained classifier and the cues from a gray image trained classifier. Both qualitative results and numeric results show that the proposed two processes effectively improve the quality of the cues. We also propose to decouple the classification loss from the loss to train a segmentation network since they have a conflict over the shared pattern regions. During the testing, we propose to use the prediction from the previously trained classifier to suppress the non-existing classes in the segmentation network output before CRF refinement, and this method steadily improves the mIoU. The performance of the overall proposed system is comparable with that of the state-of-the-art.

### References

[1] J. Ahn and S. Kwak. Learning pixel-level semantic affinity with image-level supervision for weakly supervised semantic segmentation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 4981–4990, 2018.

[2] A. Chaudhry, P. K. Dokania, and P. H. Torr. Discovering class-specific pixels for weakly-supervised semantic segmentation. arXiv preprint arXiv:1707.05821, 2017.

[3] L.-C. Chen, G. Papandreou, F. Kokkinos, K. Murphy, and A. L. Yuille. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. IEEE transactions on pattern analysis and machine intelligence, 40(4):834–848, 2018.

[4] J. Dai, K. He, and J. Sun. Bboxup: Exploiting bounding boxes to supervise convolutional networks for semantic segmentation. In Proceedings of the IEEE International Conference on Computer Vision, pages 1635–1643, 2015.

[5] M. Everingham, S. A. Eslami, L. V. Gool, C. K. Williams, J. Winn, and A. Zisserman. The pascal visual object classes challenge: A retrospective. In International journal of computer vision, pages 98–136, 2015.

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

[7] P. Fan, Q. Hou, M.-M. Cheng, G. Yu, R. R. Martin, and S.-M. Hu. Associating inter-image salient instances for weakly supervised semantic segmentation. In Proceedings of the European Conference on Computer Vision (ECCV), pages 367–383, 2018.

[8] P. F. Felzenszwalb and D. P. Huttenlocher. Efficient graph-based image segmentation. International journal of computer vision, 59(2):167–181, 2004.

[9] W. Ge, S. Yang, and Y. Yu. Multi-evidence filtering and fusion for multi-label classification, object detection and semantic segmentation based on weakly supervised learning. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 1277–1286, 2018.

[10] B. Hariharan, P. Arbeláez, L. Bourdev, S. Maji, and J. Malik. Semantic contours from inverse detectors. pages 991–998, 2011.

[11] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2016.

[12] Q. Hou, D. Massiceti, P. K. Dokania, Y. Wei, M.-M. Cheng, and P. H. Torr. Bottom-up top-down cues for weakly-supervised semantic segmentation. In International Workshop on Energy Minimization Methods in Computer Vision and Pattern Recognition, pages 263–277. Springer, 2017.

[13] Z. Huang, X. Wang, J. Wang, W. Liu, and J. Wang. Weakly-supervised semantic segmentation network with deep seeded region growing. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7014–7023, 2018.

[14] P. Isola, D. Zoran, D. Krishnan, and E. H. Adelson. Crisp boundary detection using pointwise mutual information. In European Conference on Computer Vision, pages 799–814. Springer, 2014.

[15] D. Kim, D. Cho, D. Yoo, and I. So Kweon. Two-phase learning for weakly supervised object localization. In Proceedings of the IEEE International Conference on Computer Vision, pages 3534–3543, 2017.
TABLE 1: mIoU results on the validation dataset of PASCAL VOC 2012 [2], [5] segmentation task. We test our method on two segmentation networks, the names in the first column represent the original networks where they are modified from. ResNet38 is introduced in [3], and adopted in [1]. Res50 is modified from ResNet50 in [1] by changing the last fully connected layer to a 1 × 1 convolutional layer.

| mIoU (%) | raw | snapped | merged | with prediction | with class labels | Acc % | Rec % |
|----------|-----|---------|--------|----------------|------------------|-------|-------|
| Res38    | 36.5 | 42.9    | 44.9   | 35.4           | 41.3             | 56.0  | 52.4  |
| Res50    | 33.0 | 42.7    | 49.3   | 31.1           | 41.2             | 52.4  | 48.0  |

TABLE 2: This table shows mIoU evaluation of the cues of the 10,582 trainaug images from [10]. The unknown pixels in the cues are treated as background. Both the mIoU of all the classes and that of the foreground classes are presented.

| IoU % | [16] | [22] | [15] | [1] | [27] |
|-------|------|------|------|-----|------|
| bg    | 82.9 | 83.8 | 82.8 | 88.2 | 81.6 |
| aeroplane | 82.9 | 65.2 | 62.2 | 68.2 | 64.9 |
| bike  | 26.4 | 29.4 | 23.1 | 30.6 | 25.8 |
| bird  | 61.6 | 63.8 | 65.8 | 81.1 | 71.4 |
| boat  | 27.6 | 31.2 | 21.1 | 49.6 | 29.2 |
| bus   | 66.6 | 69.6 | 71.1 | 77.8 | 75.2 |
| car   | 62.7 | 64.3 | 66.2 | 66.1 | 68.0 |
| cat   | 75.2 | 76.2 | 76.1 | 75.1 | 72.7 |
| cow   | 22.1 | 21.4 | 21.3 | 29.0 | 15.2 |
| dinnable | 28.3 | 29.8 | 35.1 | 40.2 | 33.8 |
| dog   | 65.8 | 68.2 | 70.2 | 80.4 | 56.7 |
| horse | 57.8 | 60.6 | 58.8 | 62.0 | 57.1 |
| motorbike | 62.5 | 66.2 | 62.3 | 60.9 | 67.0 |
| person | 52.5 | 55.8 | 66.1 | 73.7 | 60.7 |
| plant | 32.5 | 30.8 | 35.8 | 42.5 | 24.1 |
| sheep | 62.6 | 66.1 | 69.9 | 70.7 | 65.4 |
| sofa  | 32.1 | 34.9 | 33.4 | 42.6 | 31.5 |
| train | 45.4 | 48.8 | 45.9 | 68.1 | 43.9 |
| TV/monitor | 45.3 | 47.1 | 45.6 | 51.6 | 35.3 |
| average | 50.7 | 52.8 | 53.1 | 61.5 | 51.3 |

TABLE 3: IoU results on the validation dataset of PASCAL VOC 2012 [6], [8] segmentation task.

| IoU % | [16] | [22] | [15] | [1] | [27] |
|-------|------|------|------|-----|------|
| bg    | 83.9 | 83.7 | 83.4 | 89.1 | 83.0 |
| aeroplane | 56.4 | 58.8 | 62.2 | 70.6 | 67.3 |
| bike  | 26.4 | 29.4 | 23.1 | 30.6 | 25.8 |
| bird  | 61.6 | 63.8 | 65.8 | 81.1 | 71.4 |
| boat  | 27.6 | 31.2 | 21.1 | 49.6 | 29.2 |
| bus   | 66.6 | 69.6 | 71.1 | 77.8 | 75.2 |
| car   | 62.7 | 64.3 | 66.2 | 66.1 | 68.0 |
| cat   | 75.2 | 76.2 | 76.1 | 75.1 | 72.7 |
| cow   | 22.1 | 21.4 | 21.3 | 29.0 | 15.2 |
| dinnable | 28.3 | 29.8 | 35.1 | 40.2 | 33.8 |
| dog   | 65.8 | 68.2 | 70.2 | 80.4 | 56.7 |
| horse | 57.8 | 60.6 | 58.8 | 62.0 | 57.1 |
| motorbike | 62.5 | 66.2 | 62.3 | 60.9 | 67.0 |
| person | 52.5 | 55.8 | 66.1 | 73.7 | 60.7 |
| plant | 32.5 | 30.8 | 35.8 | 42.5 | 24.1 |
| sheep | 62.6 | 66.1 | 69.9 | 70.7 | 65.4 |
| sofa  | 32.1 | 34.9 | 33.4 | 42.6 | 31.5 |
| train | 45.4 | 48.8 | 45.9 | 68.1 | 43.9 |
| average | 50.7 | 52.8 | 53.1 | 61.5 | 51.3 |

TABLE 4: IoU results on the test dataset of PASCAL VOC 2012 [6], [8] segmentation task.

| IoU % | [16] | [22] | [15] | [1] | [27] |
|-------|------|------|------|-----|------|
| bg    | 83.9 | 83.7 | 83.4 | 89.1 | 83.0 |
| aeroplane | 56.4 | 58.8 | 62.2 | 70.6 | 67.3 |
| bike  | 26.4 | 29.4 | 23.1 | 30.6 | 25.8 |
| bird  | 61.6 | 63.8 | 65.8 | 81.1 | 71.4 |
| boat  | 27.6 | 31.2 | 21.1 | 49.6 | 29.2 |
| bus   | 66.6 | 69.6 | 71.1 | 77.8 | 75.2 |
| car   | 62.7 | 64.3 | 66.2 | 66.1 | 68.0 |
| cat   | 75.2 | 76.2 | 76.1 | 75.1 | 72.7 |
| cow   | 22.1 | 21.4 | 21.3 | 29.0 | 15.2 |
| dinnable | 28.3 | 29.8 | 35.1 | 40.2 | 33.8 |
| dog   | 65.8 | 68.2 | 70.2 | 80.4 | 56.7 |
| horse | 57.8 | 60.6 | 58.8 | 62.0 | 57.1 |
| motorbike | 62.5 | 66.2 | 62.3 | 60.9 | 67.0 |
| person | 52.5 | 55.8 | 66.1 | 73.7 | 60.7 |
| plant | 32.5 | 30.8 | 35.8 | 42.5 | 24.1 |
| sheep | 62.6 | 66.1 | 69.9 | 70.7 | 65.4 |
| sofa  | 32.1 | 34.9 | 33.4 | 42.6 | 31.5 |
| train | 45.4 | 48.8 | 45.9 | 68.1 | 43.9 |
| average | 50.7 | 52.8 | 53.1 | 61.5 | 51.3 |
Conference on Computer Vision and Pattern Recognition, pages 7268–7277, 2018.

[35] Z. Wu, C. Shen, and A. Van Den Hengel. Wider or deeper: Revisiting the resnet model for visual recognition. *Pattern Recognition*, 90:119–133, 2019.

[36] B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba. Learning deep features for discriminative localization. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2921–2929, 2016.