Class Weighted Focal Loss for Improving Class Imbalance in Semi-Supervised Object Detection

Shinichi Hoketsu[a], Tsubasa Hirakawa[b], Takayoshi Yamashita[c] and Hironobu Fujiyoshi[d]
Chubu University, 1200 Matsumoto-cho, Kasugai, Aichi, Japan

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Abstract: Object detection is a task for acquiring environmental information in automated driving. Object detection is used to detect the position and class of objects in an image. It can be made more accurate by learning with a large amount of supervised data. However, the high cost of annotating the data makes it difficult to create large supervised datasets. Therefore, research using semi-supervised learning for object detection has been attracting attention. Previous studies on semi-supervised learning in object detection tasks have mainly conducted evaluation experiments only on large datasets with many classes, such as MS COCO, and PASCAL VOC. Therefore, the effectiveness of semi-supervised learning for in-vehicle camera data as input has not yet been demonstrated. We examined the effectiveness of semi-supervised learning in object detection when in-vehicle camera data are used as input. We also proposed a class weighted focal loss that employs a unique weighting method that takes into account the class imbalance problem. Experimental results indicate that semi-supervised learning is also effective when vehicle-mounted camera images are used as input. We also confirmed that the proposed mitigates improves the class imbalance problem and improves accuracy.

1 INTRODUCTION

In the field of autonomous driving, it is essential to acquire environmental information such as the positions of surrounding vehicles and pedestrians. Object detection is used to obtain those information, which estimates the position and the class of objects existing in an image. Because of the development of deep learning techniques, various object detection methods have been developed, and the high accuracy have been achieved by using a large amount of supervised data for model training. However, building a large-scale supervised dataset requires manual annotations, which is costly due to the high annotation costs.

To achieve higher accuracy while reducing the annotation cost, semi-supervised learning has been gaining attention in recent years. Although semi-supervised learning is widely investigated in general object recognition problems, various semi-supervised object detection methods (Sohn et al., 2020; Xu et al., 2021; Chen et al., 2022; Liu et al., 2021; Liu et al., 2022) has been also proposed. In the previous research on semi-supervised learning for object detection, evaluation experiments have mainly been conducted using large-scale general object datasets such as MS COCO (Lin et al., 2015) and PASCAL VOC (Everingham et al., 2010), which contain many object classes. Meanwhile, the effectiveness of semi-supervised object detection for in-vehicle camera images has not yet been demonstrated.

In this paper, we aim to verify the effectiveness of semi-supervised object detection for in-vehicle camera images. Apart from the large-scale general object datasets, e.g., MS COCO and PASCAL VOC, in-vehicle camera image dataset has different characteristics. One of the characteristics is class imbalance problem. In-vehicle camera images are collected only on the road, which cannot be controlled. Therefore, it is difficult to adjust the number of collected samples per each object class, and the in-vehicle camera image inherently contains the class imbalance problem.

Therefore, we propose to add class weights to the classification loss in the loss of object detection model training to address the class imbalance problem, which prevents a decrease in accuracy for classes that are extremely rare in the dataset. Class weight taking into account class imbalance sets the class

[a] https://orcid.org/0009-0001-8844-5762
[b] https://orcid.org/0000-0003-3851-5221
[c] https://orcid.org/0000-0003-2631-9856
[d] https://orcid.org/0000-0001-7391-4725

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weight on the base in of the total number of objects in the dataset to optimize the object detection task. Specifically, a smaller class weight is set for classes with a large number of samples, while a larger class weight is set for classes with a small number of samples, thereby placing more emphasis on classes with a small number of samples in the loss calculation. The implementation of the optimized class weight for the object-detection task improves the class imbalance problem.

In our evaluation with BDD100K dataset (Yu et al., 2020), we demonstrate that the semi-supervised object detection is effective for in-vehicle camera images. Also, we show that our proposed loss function outperform the conventional supervised and semi-supervised approaches.

2 RELATED WORK

Herein, we briefly describe related works on supervised object detection and semi-supervised object detection methods.

2.1 Supervised Object Detection

Supervised object detection methods have been widely studied in the field of computer vision. Among various methods have been proposed, the supervised method can be categorized in to the following two types: one that uses anchor boxes (Ren et al., 2016; He et al., 2018; Lin et al., 2018; Tan and Le, 2020) and the other that is anchor-free (Tian et al., 2019; Bochkovskiy et al., 2020; Tan et al., 2020; Zhou et al., 2019). Anchor boxes-based approach are rectangular frames used to indicate regions where objects may exist. Multiple anchor boxes of different sizes and aspect ratios can be defined for each anchor on the feature map. However, the use of anchor boxes presents several problems, such as the existence of multiple hyperparameters including the number of anchor boxes, aspect ratios, and sizes, and the fact that most anchor boxes are treated as negative samples, making computation inefficient.

Various anchor-free methods have been proposed to address the disadvantages of anchor boxes fully convolutional one-stage object detection (FCOS) uses a unique index called center-ness instead of anchor boxes. Center-ness is defined as follows:

$$centerness^* = \sqrt{\frac{min(l^*, r^*)}{max(l^*, r^*)} \times \frac{min(t^*, b^*)}{max(t^*, b^*)}}, \quad (1)$$

where, l^* represents the distance from the object center to the left, r^* represents the distance to the right, t^* represents the distance to the top, and b^* represents the distance to the bottom. By using center-ness, it is possible to prevent the prediction of bounding boxes centered on positions far from the object center.

In this paper, we use the anchor free approach (i.e., FCOS) as an object detector of semi-supervised learning framework.

2.2 Semi-Supervised Object Detection

object-detection methods for semi-supervised learning framework have been proposed (Sohn et al., 2020; Xu et al., 2021; Chen et al., 2022; Liu et al., 2021; Liu et al., 2022). Major approach of semi-supervised object detection is pseudo-labeling.

One of the major pseudo-labeling approach is *self-training and the augmentation driven consistency regularization* (STAC) and the variants (Liu et al., 2021; Liu et al., 2022), which introduce strong augmentation STAC prepares two object-detection models: *teacher* and *student* and trains student model by using pseudo-labeling and strong data augmentation. In this approach, teacher is trained on labeled data only, while student is trained on both labeled and unlabeled data. The process starts with a burn-in stage, where teacher is trained. After this stage, the weights of teacher are fixed, and data are input to teacher to make predictions. Non-maximum suppression is executed to remove labels with high uncertainty, and the remaining labels are treated as pseudo-labels for student. Strong data augmentation is then applied to data similar to those predicted by teacher, and student makes predictions. The loss is calculated by comparing the predictions with the pseudo-labels, and Student is trained using this loss. This method can improve accuracy by providing a simple learning method and a large amount of unlabeled data. However, during Student's learning stage, the weight of Teacher is fixed, which means that the performance heavily depends on how accurate Teacher can be trained during the burn-in stage.

The method called Unbiased Teacher (Liu et al., 2021) is used for improving the dependency issue during the burn-in stage. Unbiased Teacher updates the weights of Teacher on the basis of the exponential moving average using Student's weights, even after the burn-in stage, which enables the feedback of Student's learned knowledge to Teacher. The updating formula for Teacher's weights using the exponential moving average is shown in Equation 2.

$$\theta_t = \alpha\theta_t + (1-\alpha)\theta_s \quad (2)$$

where, θ_t represents Teacher's weights, θ_s represents Student's weights, and α is a hyperparameter. By

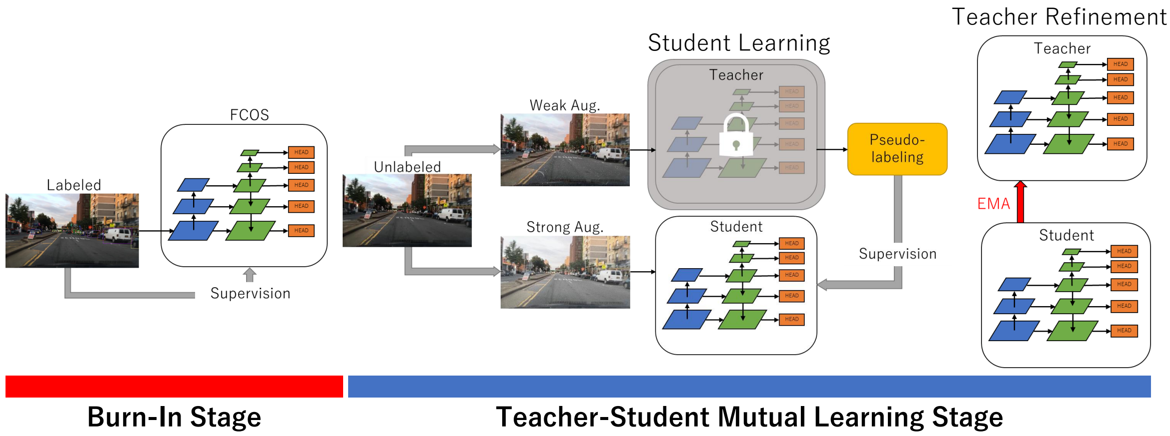


Figure 1: Overview of Unbiased Teacher v2.

gradually bringing Teacher closer to Student using the exponential moving average, Teacher can obtain Student's insights even after the burn-in stage. This improves the quality of the generated pseudo-labels.

3 METHOD

Our proposed method adopts Unbiased Teacher v2 (Liu et al., 2022) as a semi-supervised object detection framework. Unbiased Teacher v2 (Liu et al., 2022) is an improved version of Unbiased Teacher that addresses the dependency issue during the burn-in stage. Unbiased Teacher v2 is used along with the anchor-free method FCOS, which is not used in traditional semi-supervised learning. Figure 1 shows an overview of Unbiased Teacher v2. Unbiased Teacher v2 executes learning in two stages. In the burn-in stage the teacher that generates pseudo-labels is trained using only labeled data. After the burn-in stage, student is trained using the same procedure as before. However, unlike with STAC, Unbiased Teacher v2 does not initialize the model with student but uses a replica of teacher as student. Weak data augmentation is also applied to the data input to teacher, while strong data augmentation is applied to the data input to student. The loss is then calculated to obtain the gradient, which is used to update the weights of Student. After updating the weights of student, the weights of teacher are updated using exponential moving average. As data augmentations, weak data augmentation included horizontal flip, while strong data augmentation includes color transformation, grayscale, Gaussian blur, and cutout. The proposed method generates pseudo-labels in anchor-free methods and improves the learning method for detectors using the pseudo-labels. They discuss the issues with the traditional semi-supervised learning method that uses pseudo-labels and point out the uncertainty of the pseudo-labels predicted by Teacher. With Unbiased Teacher, the Teacher-predicted results are thresholded, and predictions exceeding the threshold are always treated as pseudo-labels. However, this method also treats false detections made by the Teacher as pseudo-labels, which could suppress Student's learning. To address this issue, they the proposed the Listen 2 Student mechanism. This mechanism does not update the weights if Student's prediction is correct compared with the Teacher predicted pseudo-label. This prevents the effect of false detections on Student's learning. However, it is difficult to determine whether Teacher's prediction is correct during Student's learning phase because the ground truth is not used. Therefore, the they use negative power log-likelihood loss (NPLL) (Lee et al., 2022) to evaluate whether Teacher's prediction is correct. The calculation method for NPLL is shown in Equation 3.

$$L^{sup}_{reg} = \sum_i \eta_i \left(\sum \left(\frac{(d_s - d_g)^2}{2\delta_s^2} + \frac{1}{2}\log\delta_s^2 \right) + 2\log 2\pi \right) \quad (3)$$

where, δ_s is the uncertainty of Student's prediction, d_t is Teacher's regression prediction, d_s is Student's regression prediction, and η_i is calculated by computing the mean IoU between the predicted bounding box B_s and pseudo-label B_t. The calculation method for η_i is shown in Equation 4.

$$\eta_i = \frac{B_s \cap B_t}{B_s \cup B_t} \quad (4)$$

3.1 Class Weighted Focal Loss

We propose the introduction of a unique class weight optimized for the object detection task for the class-loss function, focal loss (Lin et al., 2018) as a countermeasure against the class imbalance problem of semi-supervised learning in the object-detection task. Focal loss was mitigates the decrease in accuracy due to the imbalance between foreground and background regions in object detection tasks. However, since it is focused on foreground and background regions, it cannot be said that it performs a loss calculation that takes into account the object class. Tuning hyperparameter γ to adjust the magnitude of the loss also requires effort to be made for each dataset. A previous study (Cui et al., 2019) added class weights to focal loss in the same manner as in this study. However, that study only defined weight-setting methods for image recognition, and it is difficult to set appropriate weights for object detection.

Therefore, propose a weight setting method specific to the object-detection task to mitigate the class imbalance problem by applying a class weight set for each class to focal loss. We define the loss function with class weight added to focal loss as class weighted focal loss. The formula for calculating class weighted focal loss is shown in Equation 5.

$$CWFL(P_t) = -W_t\left((1-p_t)^{\gamma}\log(p_t)\right) \quad (5)$$

where, P_t represents the class probability, and W_t is the weight in the object class. The formula for calculating W_t is shown in Equation 6.

$$W_t = \log(\frac{C_{all}}{C_t}) \quad (6)$$

where, C_{all} is the total number of objects in all classes included in the training data, and C_t is the total number of predicted objects in the training data for the target class. We define the total number of objects as the total number of boxes in the entire training dataset. By multiplying W_t with the class loss, we can carry out learning focused on classes with fewer objects.

4 EXPERIMENTS

We the effectiveness of the proposed object-detection method by using in-vehicle camera images. We also investigated the tendencies when changing γ. Experiments will be evaluated primarily through quantitative and qualitative evaluations.

4.1 Dataset

The BDD100K dataset consists of data captured with car-mounted cameras while driving through cities such as New York, Boston, Washington DC, and San Francisco. The images were captured under various environmental conditions including clear skies, cloudy skies, rain, snow, and various times of day ranging from early morning to late night, as well as various traffic conditions ranging from congested to empty roads, resulting in a diverse dataset with many different features. The resolution of the image data is 1,280 × 740 pixels, and the dataset is comprised of 70,000 training images and 10,000 validation images.

Table 1: Number of samples per classes in the train data of BDD100K dataset.

Object class	# of samples
Person	104,611
Car	815,717
Rider	5,166
Bus	13,269
Truck	34,216
Bike	8,217
Motor	3,454
Traffic light	213,002
Traffic sign	274,594

For the object-detection task, nine classes are defined, Person, Car, Rider, Bus, Truck, Bike, Motor, Traffic light, and Traffic sign. Table 1 shows the number of objects per class in the BDD100K training data. While the Car class contains many objects, classes such as Motorcycle, Rider, and Bicycle contain relatively few objects. Additionally, while there are 70,000 training images, some classes, such as Truck and Bus, have fewer objects than this, indicating that there are many images in which certain classes are not present. Therefore, there will be a class imbalance problem, in which the model will tend to overfit to classes with many samples when trained for object detection.

4.2 Experimental Settings

We set the experimental conditions on the basis of previous research on object detection in semi-supervised learning (Sohn et al., 2020; Xu et al., 2021; Chen et al., 2022; Liu et al., 2021; Liu et al., 2022) and compared out method with semi-supervised learning and supervised learning methods.Specifically, we randomly extracted 1, 5, and 10% of the entire dataset as a supervised set and used the remaining data as an unlabeled set. When extracting supervised sets, we set the 5% set to contain 1% of the data and the 10% set to contain 5% of the data. This is because supervised sets can cause large gaps in accuracy in semi-supervised learning experiments. To account for accuracy deviations, the experiment was conducted with seed values for each of the five patterns, and comparisons were made on the basis the average accuracy.

Table 2: Comparison of supervised, semi-supervised learning, and proposed method.

	1%			5%			10%		
	AP	AP_{50}	AP_{75}	AP	AP_{50}	AP_{75}	AP	AP_{50}	AP_{75}
Supervised	13.37	27.19	11.22	20.93	42.35	17.99	23.33	45.80	20.59
Semi-supervised	**20.80**	**40.61**	**18.23**	25.64	50.01	22.28	27.71	53.21	24.64
Proposed	19.68	37.97	17.49	**26.12**	**50.42**	**23.01**	**28.20**	**53.91**	**25.23**

Table 3: Comparison of class accuracy between supervised and semi-supervised learning.

	Person	Car	Rider	Bus	Truck	Bike	Motor	Traffic light	Traffic sign
Supervised	22.81	40.54	13.55	34.02	31.52	14.24	12.38	14.69	26.26
Semi-supervised	26.95	43.29	15.59	**39.48**	**37.94**	17.58	14.56	21.34	32.70
Proposed	**27.28**	**43.63**	**16.62**	**39.48**	36.76	**18.50**	**16.77**	**21.76**	**32.98**

We used Unbiased Teacher v2 as the semi-supervised learning method for object detection. The backbone was ResNet-50 (He et al., 2015), and the detector used FCOS. We followed the settings in a previous study (Liu et al., 2022) for the data augmentation and hyperparameters used. We also used a model pre-trained on ImageNet as the pre-training model. The number of training iterations was 180,000, consisting of 30,000 iterations in the burn-in stage and 150,000 iterations in the Teacher-Student Mutual Learning stage. The batch size is set to 16, with 8 supervised and 8 unsupervised images in each batch.

The hyperparameter γ of the proposed method was set to 1, which achieved the highest accuracy in this study.

4.3 Evaluation Metrics

We used mean average precision (mAP) for evaluation, which is a performance metric that can be calculated by taking the average of precision and recall for each class. The *mAP* is defined as follows:

$$\text{mAP} = \frac{\sum_c \text{AP}_c}{N_c}. \quad (7)$$

Here, N_c is the number of object classes and average precision (AP) of class c is

$$\text{AP}_c = \int_0^1 p(r)\,dr. \quad (8)$$

where, p denotes precision, r denotes recall, c denotes class, N_c denotes the total number of classes, and AP_c denotes the AP for each class.

4.4 Quantitative Results

Table 2 shows the comparison of overall accuracy, where ”1%”, ”5%”, and ”10%” represent the percentage of labeled data in supervised learning. Note that unsupervised data are not used with the supervised learning method. The semi-supervised learning method outperformed the supervised learning method in overall accuracy, as shown in both Tables 2 and 3. This result suggests that semi-supervised learning is effective in datasets consisting only of in-vehicle camera images. In terms of the difference in AP by the percentage of labeled data shown in Table 2, the difference was 7.43 points for 1%, 4.71 points for 5%, and 4.38 points for 10%. The greater the scarcity of labeled data, the larger the difference in accuracy between supervised learning and semi-supervised learning. Therefore, semi-supervised learning is superior in situations where labeled data are scarce. Regarding the class probabilities in Table 3, it is thought that the decrease in accuracy due to class imbalance occurs in semi-supervised learning for classes such as Car, which have many samples, and classes such as Rider and Motor, which have few samples, where the difference in accuracy between supervised learning and semi-supervised learning is small.

Next, we compared a semi-supervised learning method with our proposed method. Looking at the difference in AP by the percentage of labeled data shown in Table 2, the accuracy improved when using our proposed method with 5% and 10% labeled data. However, for 1% labeled data, the accuracy of the semi-supervised method was higher, indicating that the accuracy of our proposed method decreases when the labeled data is scarce. This is because weighting the data on the basis of randomly sampled 1% causes the difference in weights between classes with few samples and those with many samples to become too large. Looking at the differences in accuracy for each class shown in Table 3, our proposed method achieves higher accuracy for all classes except for Truck and Bus. The reason the accuracy did not improve for these classes may be that they share similar features

Table 4: Accuracy comparison for different γ.

	1%			5%			10%		
γ	AP	AP_{50}	AP_{75}	AP	AP_{50}	AP_{75}	AP	AP_{50}	AP_{75}
0	17.72	33.77	15.90	24.53	47.47	21.86	26.64	50.45	24.20
1	**19.68**	**37.97**	**17.49**	**26.12**	50.42	**23.01**	**28.20**	**53.91**	**25.23**
2	19.44	38.02	17.14	26.04	**50.47**	22.97	27.93	53.78	24.64
3	19.35	37.17	17.19	25.35	49.15	22.24	27.78	52.91	24.89

Table 5: Accuracy comparison by class for different Gamma.

γ	Person	Car	Rider	Bus	Truck	Bike	Motor	Traffic light	Traffic sign
0	26.68	42.92	15.26	38.07	34.33	18.34	16.12	18.59	29.44
1	**27.28**	**43.63**	**16.62**	39.48	36.76	18.50	**16.77**	**21.76**	**32.98**
2	27.20	43.27	15.93	40.19	**38.16**	**18.59**	16.20	20.90	30.94
3	26.91	43.39	15.11	**40.73**	38.02	17.97	14.62	20.97	32.25

with the Car class and weighting alone is not sufficient to distinguish them.

4.5 Effect of γ

We investigated the effects of changing γ with our proposed method. Table 4 shows the comparison of accuracy for different percentages of labeled data, while Table 5 shows the comparison of class-wise accuracy when the labeled data were 10%. Based on the results in Table 4, except for AP50 when labeled data were 5%, the highest accuracy was achieved when γ was set to 1. Therefore, it can be concluded that setting γ to 1 is appropriate. However, as we can see from Table 5, for the Bus, Truck, and Bike classes, the highest accuracy was achieved when γ was set to 2 or 3. This is because as γ increases, the loss for classes that are similar to the correct class, such as Bus and Truck, is almost ignored even if their confidence scores are not high. This helps improve the learning of Bus and Truck. Similarly for Bike class, the loss is also almost ignored when the features are similar to those of the Motor class.

4.6 Qualitative Results

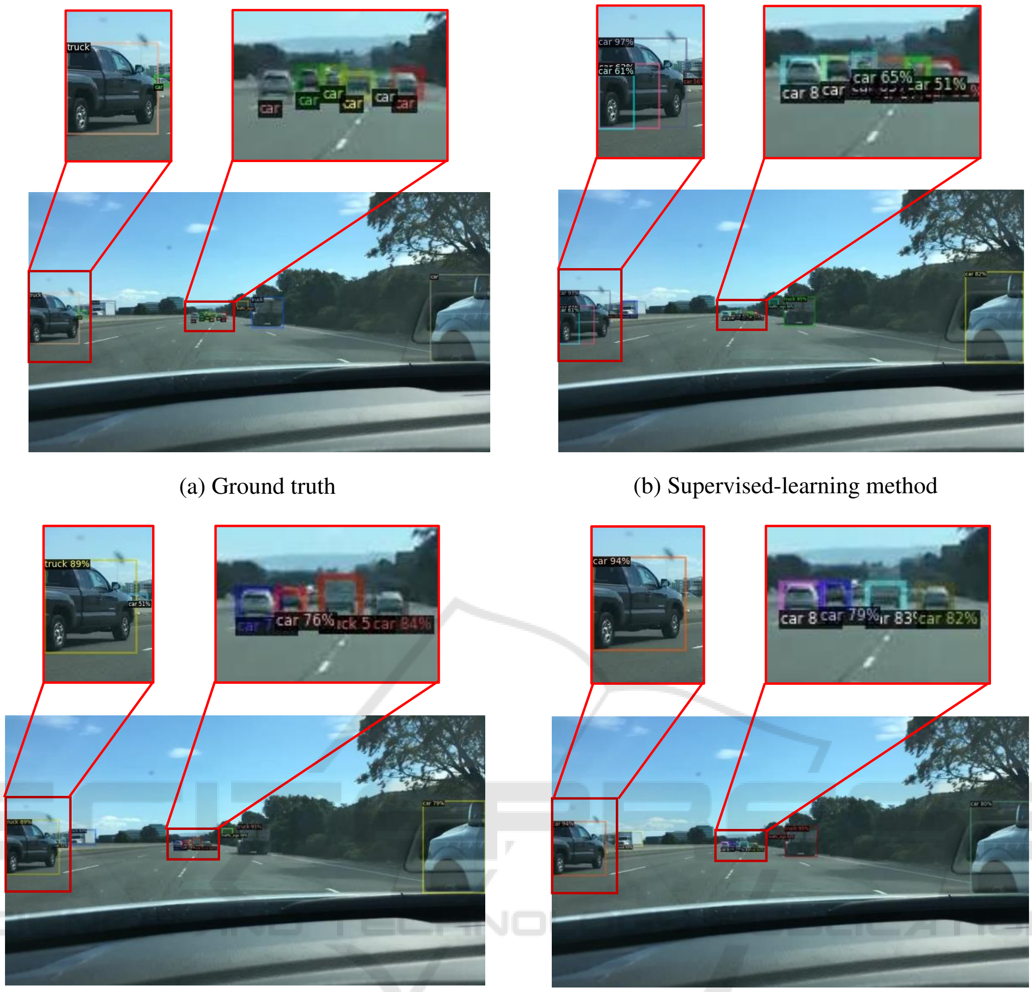
Qualitative evaluation is shown in Figure 2, 3. With the supervised-learning method (Figure 2b), the Truck on the left side of the image was misclassified as a Car and a false detection is made around the tire area. With the semi-supervised-learning method (Figure 2c), a Car was not detected in the center back. However, the proposed method (Figure 2d) suppressed false detections for the Truck on the left side of the image and correctly detected the Car in the center back. When comparing the proposed method (Figure 2d) with the semi-supervised-learning method (Figure 2c), the proposed method detected objects with higher class probabilities than the semi-supervised method. However, the proposed method misclassified the Truck on the left side of the image as a Car(Figure 2d). Therefore, the proposed method is not able to acquire features that can distinguish Trucks similar to Cars through semi-supervised learning.

In a different scenario, as shown in Figure 3, when a rider on a motorcycle is positioned in the center of the screen, it becomes evident that only the proposed method correctly detects them. Furthermore, the proposed method enables the detection of individuals attempting to cross a pedestrian crossing. This demonstrates that using the proposed method allows for the improved detection rate of minority classes, as evident through qualitative assessment.

5 CONCLUSION

In this paper, we focus on the semi-supervised object detection of in-vehicle camera images and we proposed class weighted focal loss. Our method is based on pseudo-labeling approach (Unbiased Teacher v2) and we introduce the focal loss weighted by class balances in the training dataset. This enables us to improve detection accuracy on a rare object classes.

In the experiments, we used BDD100K as the in-vehicle camera image dataset and evaluated the effectiveness of the proposed method. The proposed method showed improved accuracy compared with conventional supervised- and semi-supervised-learning object-detection methods except in cases where the teacher data was 1%. Since the proposed



(a) Ground truth

(b) Supervised-learning method

(c) Semi-supervised-learning method

(d) Proposed ($\gamma = 1$)

Figure 2: Example of Visualization of Object Detection.

method calculates weights on the basis the number of samples in the dataset, it enables learning that emphasizes classes with fewer samples. However, we found that simply adding weights does not sufficiently distinguish between classes with similar characteristics in some cases, and this does not lead to improved accuracy in certain classes. Future work includes establishing appropriate class-weight settings and a learning method focused on fewer samples.

REFERENCES

Bochkovskiy, A., Wang, C.-Y., and Liao, H.-Y. M. (2020). Yolov4: Optimal speed and accuracy of object detection.

Chen, B., Li, P., Chen, X., Wang, B., Zhang, L., and Hua, X.-S. (2022). Dense learning based semi-supervised object detection.

Cui, Y., Jia, M., Lin, T., Song, Y., and Belongie, S. J. (2019). Class-balanced loss based on effective number of samples. *CoRR*, abs/1901.05555.

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

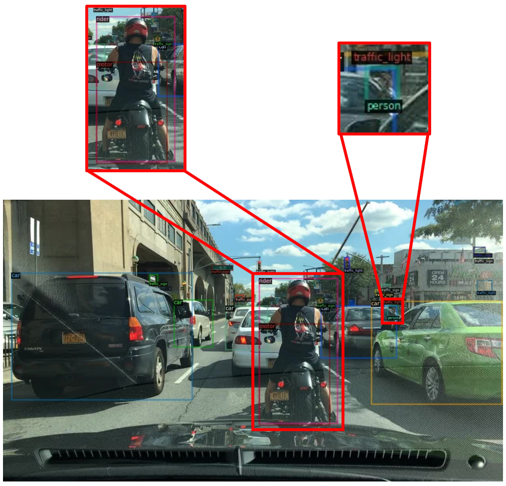
He, K., Gkioxari, G., Dollár, P., and Girshick, R. (2018). Mask r-cnn.

He, K., Zhang, X., Ren, S., and Sun, J. (2015). Deep residual learning for image recognition.

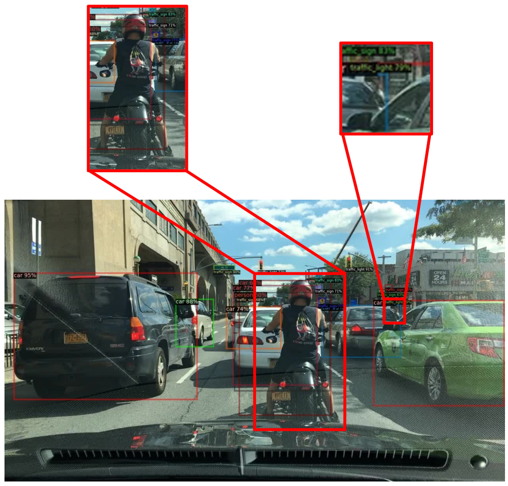
Lee, Y., won Hwang, J., Kim, H.-I., Yun, K., Kwon, Y., Bae, Y., and Hwang, S. J. (2022). Localization uncertainty estimation for anchor-free object detection.

Lin, T.-Y., Goyal, P., Girshick, R., He, K., and Dollár, P. (2018). Focal loss for dense object detection.

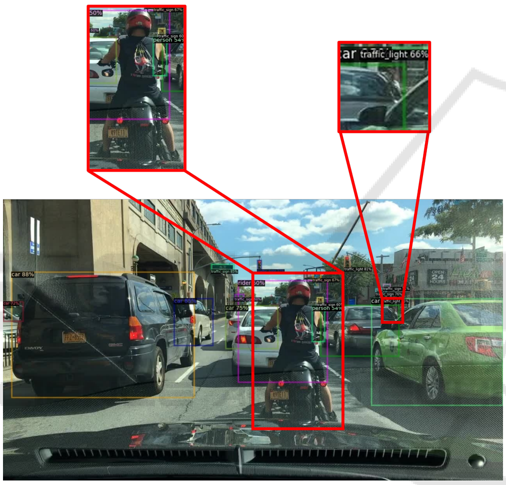
Lin, T.-Y., Maire, M., Belongie, S., Bourdev, L., Girshick,



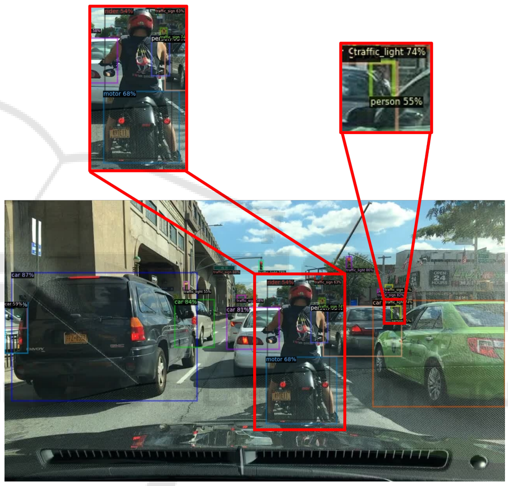
(a) Ground truth



(b) Supervised-learning method



(c) Semi-supervised-learning method



(d) Proposed ($\gamma = 1$)

Figure 3: Visualization Example with Rider.

R., Hays, J., Perona, P., Ramanan, D., Zitnick, C. L., and Dollár, P. (2015). Microsoft coco: Common objects in context.

Liu, Y.-C., Ma, C.-Y., He, Z., Kuo, C.-W., Chen, K., Zhang, P., Wu, B., Kira, Z., and Vajda, P. (2021). Unbiased teacher for semi-supervised object detection.

Liu, Y.-C., Ma, C.-Y., and Kira, Z. (2022). Unbiased teacher v2: Semi-supervised object detection for anchor-free and anchor-based detectors.

Ren, S., He, K., Girshick, R., and Sun, J. (2016). Faster r-cnn: Towards real-time object detection with region proposal networks.

Sohn, K., Zhang, Z., Li, C., Zhang, H., Lee, C., and Pfister, T. (2020). A simple semi-supervised learning framework for object detection. *CoRR*, abs/2005.04757.

Tan, M. and Le, Q. V. (2020). Efficientnet: Rethinking model scaling for convolutional neural networks.

Tan, M., Pang, R., and Le, Q. V. (2020). Efficientdet: Scalable and efficient object detection.

Tian, Z., Shen, C., Chen, H., and He, T. (2019). Fcos: Fully convolutional one-stage object detection.

Xu, M., Zhang, Z., Hu, H., Wang, J., Wang, L., Wei, F., Bai, X., and Liu, Z. (2021). End-to-end semi-supervised object detection with soft teacher.

Yu, F., Chen, H., Wang, X., Xian, W., Chen, Y., Liu, F., Madhavan, V., and Darrell, T. (2020). Bdd100k: A diverse driving dataset for heterogeneous multitask learning.

Zhou, X., Wang, D., and Krähenbühl, P. (2019). Objects as points.