Woodscape Fisheye Object Detection for Autonomous Driving  
– CVPR 2022 OmniCV Workshop Challenge

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Abstract—Object detection is a comprehensively studied problem in autonomous driving. However, it has been relatively less explored in the case of fisheye cameras. The strong radial distortion breaks the translation invariance inductive bias of Convolutional Neural Networks. Thus, we present the WoodScape fisheye object detection challenge for autonomous driving which was held as part of the CVPR 2022 Workshop on Omnidirectional Computer Vision (OmniCV). This is one of the first competitions focused on fisheye camera object detection. We encouraged the participants to design models which work natively on fisheye images without rectification. We used Codalab to host the competition based on the publicly available WoodScape fisheye dataset. In this paper, we provide a detailed analysis on the competition which attracted the participation of 120 global teams and a total of 1492 submissions. We briefly discuss the details of the winning methods and analyze their qualitative and quantitative results.

I. INTRODUCTION

Autonomous Driving is a challenging problem and it requires multiple sensors handling different aspects and robust sensor fusion algorithms which combine the sensor information effectively [1]–[3]. Surround-view systems employ four sensors to create a network with large overlapping zones to cover the car’s near-field area [4], [5]. For near-field sensing, wide-angle images reaching 180° are utilized. Any perception algorithm must consider the substantial fisheye distortion that such camera systems produce. Because most computer vision research relies on narrow field-of-view cameras with modest radial distortion, this is a substantial challenge. However, because camera systems are now more commonly used, development in this field has been attained. Figure 1 illustrates the typical automotive surround-view camera system comprising of four fisheye cameras covering the entire 360° around the vehicle. Most commercial cars have fisheye cameras as a primary sensor for automated parking. Rear-view fisheye cameras have become a typical addition in low-cost vehicles for dashboard viewing and reverse parking. Despite its abundance, there are just a few public databases for fisheye images, so relatively little research is conducted. One such dataset is the Oxford RobotCar [6] a large-scale dataset focusing on the long-term autonomy of autonomous vehicles. The key responsibilities of this dataset, which enables research into continuous learning for autonomous cars and mobile robotics, are localization and mapping. It includes approximately 100 repetitions of a continuous route around Oxford, UK, collected over a year and commonly used for long-term localization and mapping.

WoodScape [7] is a large dataset for 360° sensing around an ego vehicle with four fisheye cameras. It is designed to complement existing automobile datasets with limited FOV images and encourage further research in multi-task multicamera computer vision algorithms for self-driving vehicles. It is built based on industrialization needs addressing the diversity challenges [8]. The dataset sensor configuration consists of four surround-view fisheye cameras sampled randomly. The dataset comprises labels for geometry and segmentation tasks, including semantic segmentation, distance estimation, generalized bounding boxes, motion segmentation, and a novel lens soiling detection task (shown in Figure 2).

Instead of naive rectification, the WoodScape pushes researchers to create solutions that can work directly on raw fisheye images, modeling the underlying distortion. WoodScape dataset (public and private versions) has enabled research in various perception areas such as object detection [9]–[12], trailer detection [13], soiling detection [14]–[16], semantic segmentation [17]–[21], weather classification [22], depth prediction [23]–[29], moving object detection.

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TABLE 1. Details of start and end dates of the two phases of the challenge.

| Phase | Start Date | End Date | Duration |
|-------|------------|----------|----------|
| Dev   | April 15   | June 3   | 50 days  |
| Test  | June 4     | June 5   | 2 days   |

TABLE 2. Train and test data split of the dataset samples.

| Split        | Images | Percent  |
|--------------|--------|----------|
| Training Set | 8234   | 82.34%   |
| Test Set     | 1766   | 17.66%   |
| Total        | 10000  | 100.00%  |

TABLE 3. Class labels 0-4 and their corresponding objects.

| Label | Description   |
|-------|---------------|
| 0     | Vehicles      |
| 1     | Person        |
| 2     | Bicycle       |
| 3     | Traffic Light |
| 4     | Traffic Sign  |

A. Metrics

Mean Average Precision (mAP) is a standard evaluation metric for object detection tasks, which first computes the Average Precision (AP) for each class and then computes the average over classes.

For each image in the test set, the correspondence for a ground truth bounding box is established by choosing the bounding box that has the maximum IoU among all propose bounding boxes. Each bounding box is then categorized as either TP (True Positive) or FP (False Positive). Correspondences matching is done without replacement to avoid one-to-many correspondences. A bounding box proposed is considered as an TP if it has an IoU (Intersection over Union) of more than the IoU Threshold 0.5 with the corresponding ground truth bounding box, and is marked an FP if less. Intersection of Union for two bounding boxes is defined as:

\[
\text{IoU} = \frac{\text{Area of Intersection}}{\text{Area of Union}}
\]

The competition entries in CodaLab were evaluated and ordered based on mAP, averaged to all 5 classes. Along with the overall rank based on mAP, rank based on AP for individual classes are also displayed in the leaderboard.

B. Reward

The winning team will receive €1,000 through sponsorship from Lero and will be offered to present in-person or virtually in the OmniCV 3rd Workshop held in conjunction with IEEE Computer Vision and Pattern Recognition (CVPR) 2022.

C. Conditions

Competition rules allowed the teams to make use of any other public datasets for pre-training. There were no restrictions on computational complexity as well. There is no limit on team size but there is a limit of 10 submissions per day and 150 submissions in total for a team. For the Test phase, submissions were limited to a maximum of 2. Valeo employees or their collaborators who have access to the full WoodScape dataset were not allowed to take part in this challenge.

III. Outcome

The competition was active for 52 days from April 27, 2022 through to June 5, 2022. The competition attracted a total of 120 global teams with 1492 submissions. Illustration of the trend of number of daily submissions and their scores during the entire phase of the competition is shown in Figure 4. Interestingly, over 93.57% of submissions were...
recorded on or after the fourth week, and over 80.63% of
the submissions were recorded during the second half. It
can be seen from the graph that during the third week, the
number of submissions per day increased gradually to about
40. Since the fourth week, the challenge received an average
45 submissions per day. There was at least one submission
in the second half of the challenge with score greater than
0.45 making their way to the top 10 in the leaderboard with
some exceptions.

A. Methods

1) Winning Team: Team **GroundTruth** finished in first
place with a score of 0.51 (Vehicles 0.67, Person 0.58,
Bicycle 0.44, Traffic Light 0.50, Traffic Sign 0.33) with their
Multi-Head Self-Attention (MHSA) Dark Blocks approach.
Xiaojianqng Lu, Tong Gou, Yuxing Li, Hao Tan, Guojin
Cao, and Licheng Jiao affiliated to Guangzhou Institute of
Technology, Key Laboratory of Intelligent Perception and
Image Understanding of Ministry of Education, Xidian Uni-
versity, and School of Water Conservancy and Hydropower,
Xi’an University of Technology belonged to this team. In
the individual class scores, they achieved first place for
Bicycle class, and second place for the rest of the classes.
They adapt the original CSP Darknet [39] backbone by
introducing MHSA layers replacing the CSP bottleneck and
with 3x3 and 1x1 spatial convolutional layers. They use a
weighted Bidirectional Feature Pyramid Network (BiFPN)
[40] to process multi-scale features. They further improve
the detection accuracy using Test Time Augmentation (TTA)
and Model Soups [41]. In more detail, multiple augmented
copies of each image is generated during inference and
bounding boxes predicted by the network for all such copies
are returned. They additionally train Scaled-YOLOv4 [42]
models and use Model Soups ensemble method too enhance
the predictions. This resulted in achieving the top score of
0.51.

2) Second Place: Team **heboyong** finished in second
place with a score of 0.50 (Vehicles 0.67, Person 0.58,
Bicycle 0.37, Traffic Light 0.53, Traffic Sign 0.36) using
Swin Transformers. He Boyong, Guo Weijie, Ye Qianwen,
and Li Xianjiang affiliated to Xiamen University belonged
to this team. In the individual class scores, they achieved
first place for all classes except Bicycle class for which
they ranked sixth. They use Cascade RCNN [43] with a SwinTransformer [44] backbone. They utilize CBNetv2 [45] network architecture to improve accuracy of the Swin Transformer backbone without retraining and use Seesaw Loss [46] to address the long-tailed problem that occurs between the categories of quantitative imbalance. They use MixUp
In Figure 5, we illustrate outputs of the top 3 teams from OmniCV Workshop, CVPR 2022, held on June 20, 2022. GroundTruth team with details of the top twenty team participants. The winning team IPIU-XDU finished in third place with a score of 0.49 (Vehicles 0.67, Person 0.58, Bicycle 0.40, Traffic Light 0.50, Traffic Sign 0.32) using Swin Transformer networks. Chenghui Li, Chao Li, Xiao Tan, Zhongjian Huang, and Yuting Yang affiliated to Hangzhou Institute of Technology, Xidian University belonged to this team. In the individual class scores, they achieved second place for Bicycle class, and third place for the rest of the classes. They utilize Swin Transformer v2 [51] with HTC++ (Hybrid Task Cascade) [52] [44] to detect objects in fisheye images. They use multi-scale training with ImageNet-22K [53] pretrained backbone with its learning rate set to one-tenth of that of the head and use Soft-NMS [50] for inference. An ensemble architecture is used to boost the scores, the confidence scores of bounding boxes proposed by each model is used and averaged using Weighted Boxes Fusion [54].

B. Results and Discussion

Team GroundTruth, with a lead score of 0.51 (Vehicles 0.67, Person 0.58, Bicycle 0.44, Traffic Light 0.50, Traffic Sign 0.33), was announced as the winner on 6th June 2022. In Table 4, we showcase the challenge leaderboard with details of the top twenty team participants. The winning team GroundTruth presented their method virtually in the OmniCV Workshop, CVPR 2022, held on June 20, 2022. In Figure 5, we illustrate outputs of the top 3 teams from randomly picked samples.

IV. Conclusion

In this paper, we discussed the results of the fisheye object detection challenge hosted at our CVPR OmniCV workshop 2022. Spatially variant radial distortion makes the object detection task quite challenging. In addition, bounding boxes are sub-optimal representations of objects particularly at periphery which have a curved box shape. Most solutions submitted did not explicitly make use of the radial distortion model to exploit the known camera model. The top performing methods made use of transformers which seem to learn the radial distortion implicitly. Extensive augmentation methods were also used. We have started accepting submissions again keeping the challenge open to everyone to encourage further research and novel solutions to fisheye object detection. In our future work, we plan to organize similar workshop challenges on fisheye camera multi-task learning.

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REFERENCES

[1] R. Yadav, A. Samir, H. Rashed, S. Yogamani, and R. Dahyot, “Cnn based color and thermal image fusion for object detection in automated driving,” Irish Machine Vision and Image Processing, 2020.

[2] S. Mohapatra, S. Yogamani, H. Gotzig, S. Milz, and P. Mader, “Bevdetnet: bird’s eye view lidar point cloud based real-time 3d object detection for autonomous driving,” in 2021 IEEE International Intelligent Transportation Systems Conference (ITSC). IEEE, 2021, pp. 2809–2815.

[3] K. Dasgupta, A. Das, U. Bhattacharya, and S. Yogamani, “Spatio-contextual deep network-based multimodal pedestrian detection for autonomous driving,” IEEE Transactions on Intelligent Transportation Systems, 2022.

TABLE 4. Snapshot of the challenge leaderboard illustrating the top twenty participants based on the mAP Score metric. Top three participants are highlighted in shades of green.
[4] C. Eising, J. Horgan, and S. Yogamani, “Near-field perception for low-speed vehicle automation using surround-view fisheye cameras,” IEEE Transactions on Intelligent Transportation Systems, 2021.

[5] V. R. Kumar, C. Eising, C. Witt, and S. Yogamani, “Surround-view fisheye camera perception for automated driving: Overview, survey and challenges,” arXiv preprint arXiv:2205.13281, 2022.

[6] W. Maddern, G. Pascoe, C. Linegar, and P. Newman, “I, year, 1000 km: The Oxford robotcar dataset,” The International Journal of Robotics Research, vol. 36, no. 1, pp. 3–15, 2017.

[7] S. Yogamani, C. Hughes, J. Horgan, G. Sistu, P. Varley, D. O’Dea, M. Uricár, S. Milz, M. Simon, K. Amende, et al., “Woodscape: A multicamera fisheye dataset for autonomous driving,” in Proceedings of the IEEE/CVF International Conference on Computer Vision (CVPR), 2019, pp. 9308–9318.

[8] M. Uricár, D. Hurych, P. Křízek, et al., “Challenges in designing datasets and validation for autonomous driving,” in Proceedings of the International Conference on Computer Vision Theory and Applications, 2019.

[9] A. Dahal, V. R. Kumar, S. Yogamani, et al., “An online learning system for wireless charging alignment using surround-view fisheye cameras,” IEEE Robotics and Automation Letters, 2021.

[10] H. Rashed, E. Mohamed, G. Sistu, et al., “FisheyeYOLO: Object Detection on Fisheye Cameras for Autonomous Driving,” Machine Learning for Autonomous Driving NeurIPS, 2020.

[11] H. Rashed, E. Mohamed, G. Sistu, V. R. Kumar, C. Eising, A. El-Sallab, and S. Yogamani, “Generalized object detection on fisheye cameras for autonomous driving: Dataset, representations and baseline,” in Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2021, pp. 2272–2280.

[12] L. Yahiaoui, C. Hughes, J. Horgan, et al., “Optimization of ISP parameters for object detection algorithms,” Electronic Imaging, vol. 2019, no. 15, pp. 44–1, 2019.

[13] A. Dahal, J. Hossen, C. Sumanth, G. Sistu, K. Malhan, M. Amasha, and S. Yogamani, “Deeptrailerrassit: Deep learning based trailer detection, tracking and articulation angle estimation on automotive rear-view camera,” in Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops, 2019, pp. 0–0.

[14] M. Uricár, G. Sistu, H. Rashed, A. Vobeczy, V. R. Kumar, P. Křízek, F. Burger, and S. Yogamani, “Let’s get dirty: Gan based data augmentation for camera lens soiling detection in autonomous driving,” in Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision, 2021, pp. 766–775.

[15] A. Das, P. Křízek, G. Sistu, et al., “Tiledsoilingnet: Tile-level soiling detection on automotive surround-view cameras using coverage metric,” in Proceedings of the International Conference on Intelligent Transportation Systems, 2020, pp. 1–6.

[16] M. Uricár, J. Ulicny, G. Sistu, et al., “Desoiling dataset: Restoring soiled areas on automotive fisheye cameras,” in Proceedings of the International Conference on Computer Vision Workshops. IEEE, 2019, pp. 4273–4279.

[17] R. Cheke, G. Sistu, C. Eising, P. van de Ven, V. R. Kumar, and S. Yogamani, “FisheyePIXpro: self-supervised pretrained using fisheye images for semantic segmentation,” in Electronic Imaging, Autonomous Vehicles and Machines Conference 2022, 2022.

[18] I. Sobh, A. Hamed, V. Ravi Kumar, et al., “Adversarial attacks on multi-task visual perception for autonomous driving,” Journal of Imaging Science and Technology, vol. 65, no. 6, pp. 60408–1, 2021.

[19] A. Dahal, E. Golab, R. Garlapati, et al., “RoadEdgeNet: Road Edge Detection System Using Surround View Camera Images,” in Electronic Imaging. Society for Imaging Science and Technology, 2021.

[20] M. Klingner, V. R. Kumar, S. Yogamani, A. Bär, and T. Fingscheidt, “Detecting adversarial perturbations in multi-task perception,” arXiv preprint arXiv:2203.01177, 2022.

[21] H. Rashed, A. El-Sallab, S. Yogamani, et al., “Motion and depth augmented semantic segmentation for autonomous navigation,” in Proceedings of the Computer Vision and Pattern Recognition Conference Workshops, 2019, pp. 364–370.

[22] M. M. Dhananjaya, V. R. Kumar, and S. Yogamani, “Weather and Light Level Classification for Autonomous Driving: Dataset, Baseline and Active Learning,” in Proceedings of the International Conference on Intelligent Transportation Systems. IEEE, 2021.

[23] V. Ravi Kumar, S. Milz, C. Witt, et al., “Monocular fisheye camera depth estimation using sparse lidar supervision,” in Proceedings of the International Conference on Intelligent Transportation Systems, 2018, pp. 2853–2858.

[24] V. Ravi Kumar, S. Milz, C. Witt, et al., “Near-field depth estimation using monocular fisheye camera: A semi-supervised learning approach using sparse LiDAR data,” in Proceedings of the Computer Vision and Pattern Recognition Conference Workshops, vol. 7, 2018.

[25] V. R. Kumar, M. Klingner, S. Yogamani, et al., “SYDistNet: Self-Supervised Near-Field Distance Estimation on Surround View Fisheye Cameras,” Transactions on Intelligent Transportation Systems, 2021.

[26] V. Ravi Kumar, S. Yogamani, M. Bach, et al., “UnRectDepthNet: Self-Supervised Monocular Depth Estimation using a Generic Framework for Handling Common Camera Distortion Models,” in Proceedings of the International Conference on Intelligent Robots and Systems, 2020, pp. 8177–8183.

[27] V. Ravi Kumar, S. A. Hiremath, M. Bach, et al., “Fisheyedistnet: Self-supervised scale-aware distance estimation using monocular fisheye camera for autonomous driving,” in Proceedings of the International Conference on Robotics and Automation, 2020, pp. 574–581.

[28] V. Ravi Kumar, S. Yogamani, S. Milz, et al., “FisheyeDistanceNet++: Self-Supervised Fisheye Distance Estimation with Self-Attention, Robust Loss Function and Camera View Generalization,” in Electronic Imaging. Society for Imaging Science and Technology, 2021.

[29] V. Ravi Kumar, M. Klingner, S. Yogamani, et al., “Syndistnet: Self-supervised monocular fisheye camera distance estimation synergized with semantic segmentation for autonomous driving,” in Proceedings of the Workshop on Applications of Computer Vision, 2021, pp. 61–71.

[30] M. Siam, H. Mahgoub, M. Zahran, S. Yogamani, M. Jagersand, and A. El-Sallab, “Modnet: Motion and appearance guided object detection network for autonomous driving,” in 2018 21st International Conference on Intelligent Transportation Systems (ITSC). IEEE, 2018, pp. 2859–2864.

[31] M. Yahiaoui, H. Rashed, L. Mariotti, et al., “FisheyeMODeNet: Moving Object Detection on Surround-view Cameras for Autonomous Driving,” in Proceedings of the Irish Machine Vision and Image Processing, 2019.

[32] E. Mohamed, M. Ewaisha, M. Siam, et al., “Monocular instance motion segmentation for autonomous driving: Kitti instancemots dataset and multi-task baseline,” in Proceedings of the Intelligent Vehicles Symposium. IEEE, 2021, pp. 114–121.

[33] N. Tripathi and S. Yogamani, “Trained trajectory based automated parking system using Visual SLAM,” in Proceedings of the Computer Vision and Pattern Recognition Conference Workshops, 2021.

[34] L. Gallagher, V. R. Kumar, S. Yogamani, and J. B. McDonald, “A hybrid sparse-dense monocular slam system for autonomous driving,” in 2021 European Conference on Mobile Robots (ECMR). IEEE, 2021, pp. 1–8.

[35] I. Leang, G. Sistu, F. Bürger, et al., “Dynamic task weighting methods for multi-task networks in autonomous driving systems,” in Proceedings of the International Conference on Intelligent Transportation Systems. IEEE, 2020, pp. 1–8.

[36] V. R. Kumar, S. Yogamani, H. Rashed, G. Sistu, I. Leang, S. Milz, and P. Mader, “ Omnident: Surround view cameras based multi-task visual perception network for autonomous driving,” IEEE Robotics and Automation Letters, vol. 6, no. 2, pp. 2830–2837, 2021.

[37] A. R. Sekkat, Y. Dupuis, V. R. Kumar, H. Rashed, S. Yogamani, P. Vasseur, and P. Honeine, “Synwoodscape: Synthetic surround-view fisheye camera dataset for autonomous driving,” arXiv preprint arXiv:2203.05056, 2022.

[38] S. Ramachandran, G. Sistu, J. McDonald, and S. Yogamani, “Woodscape fisheye semantic segmentation for autonomous driving—cvpr 2021 omniv workshop challenge,” arXiv preprint arXiv:2107.08246, 2021.

[39] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, “Yolov4: Optimal speed and accuracy of object detection,” 2020.

[40] M. Tan, R. Pang, and Q. V. Le, “Efficientdet: Scalable and efficient object detection,” in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2020, pp. 10 781–10 790.

[41] M. Wortsman, G. Ilharco, S. Y. Gadre, R. Roelofs, R. Gontijo-Lopes, A. S. Morcos, H. Namkoong, A. Farhadi, Y. Carmon, S. Kornblith, et al., “Model soups: averaging weights of multiple fine-tuned models improves accuracy without increasing inference time,” arXiv preprint arXiv:2203.05482, 2021.

[42] C.-Y. Wang, A. Bochkovskiy, and H.-Y. M. Liao, “Scaled-yolov4: Scaling cross stage partial network,” in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2021, pp. 13 029–13 038.
[43] Z. Cai and N. Vasconcelos, “Cascade r-cnn: Delving into high quality object detection,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 6154–6162.

[44] Z. Liu, Y. Lin, Y. Cao, H. Hu, Y. Wei, Z. Zhang, S. Lin, and B. Guo, “Swin transformer: Hierarchical vision transformer using shifted windows,” in *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 2021, pp. 10012–10022.

[45] T. Liang, X. Chu, Y. Liu, Y. Wang, Z. Tang, W. Chu, J. Chen, and H. Ling, “C3netv2: A composite backbone network architecture for object detection,” *arXiv preprint arXiv:2107.00420*, 2021.

[46] J. Wang, W. Zhang, Y. Zang, Y. Cao, J. Pang, T. Gong, K. Chen, Z. Liu, C. C. Loy, and D. Lin, “Seesaw loss for long-tailed instance segmentation,” in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 2021, pp. 9695–9704.

[47] H. Zhang, M. Cisse, Y. N. Dauphin, and D. Lopez-Paz, “mixup: Beyond empirical risk minimization,” in *6th International Conference on Learning Representations, ICLR 2018*, 2018.

[48] A. Buslaev, V. I. Iglovikov, E. Khvedchenya, A. Parinov, M. Druzhinin, and A. A. Kalinin, “Albumentations: fast and flexible image augmentations,” *Information*, vol. 11, no. 2, p. 125, 2020.

[49] P. Izmailov, D. Podoprikhin, T. Garipov, D. Vetrov, and A. G. Wilson, “Averaging weights leads to wider optima and better generalization,” *arXiv preprint arXiv:1803.05407*, 2018.

[50] N. Bodla, B. Singh, R. Chellappan, and L. S. Davis, “Soft-nms–improving object detection with one line of code,” in *Proceedings of the IEEE international conference on computer vision*, 2017, pp. 5561–5569.

[51] Z. Liu, H. Hu, Y. Lin, Z. Yao, Z. Xie, Y. Wei, J. Ning, Y. Cao, Z. Zhang, L. Dong, *et al.*, “Swin transformer v2: Scaling up capacity and resolution,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022, pp. 12009–12019.

[52] K. Chen, J. Pang, J. Wang, Y. Xiong, X. Li, S. Sun, W. Feng, Z. Liu, J. Shi, W. Ouyang, *et al.*, “Hybrid task cascade for instance segmentation,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2019, pp. 4974–4983.

[53] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “Imagenet: A large-scale hierarchical image database,” in *2009 IEEE conference on computer vision and pattern recognition*. Ieee, 2009, pp. 248–255.

[54] R. Solovyev, W. Wang, and T. Gabruseva, “Weighted boxes fusion: Ensembling boxes from different object detection models,” *Image and Vision Computing*, vol. 107, p. 104117, 2021.