

# EFFICIENT ADAPTATION FOR REMOTE SENSING VISUAL GROUNDING

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**Abstract**—Foundation models have revolutionized artificial intelligence (AI), offering remarkable capabilities across multi-modal domains. Their ability to precisely locate objects in complex aerial and satellite images, using rich contextual information and detailed object descriptions, is essential for remote sensing (RS). These models can associate textual descriptions with object positions through the Visual Grounding (VG) task, but due to domain-specific challenges, their direct application to RS produces sub-optimal results.

To address this, we applied Parameter Efficient Fine Tuning (PEFT) techniques to adapt these models for RS-specific VG tasks. Specifically, we evaluated LoRA placement across different modules in Grounding DINO and used BitFit and adapters to fine-tune the OFA foundation model pre-trained on general-purpose VG datasets. This approach achieved performance comparable to or surpassing current State Of The Art (SOTA) models while significantly reducing computational costs.

This study highlights the potential of PEFT techniques to advance efficient and precise multi-modal analysis in RS, offering a practical and cost-effective alternative to full model training.

**Index Terms**—Remote Sensing, Visual Grounding, Foundation Models, Parameter-Efficient Fine-Tuning.

## I. INTRODUCTION

Foundation models have changed the field of artificial intelligence by demonstrating remarkable adaptability in different areas. These models, pre-trained on vast datasets, excel in multi-modal tasks by integrating diverse modalities such as textual, visual, audio, video, and sensory data. Their ability to generalize across diverse applications has solidified their role as a foundation for the advancement of AI research and practical implementations. Although models such as Grounding DINO[1] and One-For-ALL(OFA)[2] have shown promise in general multi-modality and more specifically visual grounding tasks, their direct application to remote sensing (RS) remains limited. This paper focuses on adapting these powerful models to the unique challenges and data characteristics of RS, enabling their effective use for satellite and aerial imagery analysis.

Visual grounding(VG), a process designed to identify and localize objects or regions within an image based on natural language descriptions, has advanced significantly; however,

their application to the remote sensing (RS) domain remains underexplored. These models struggle when dealing with RS imagery due to its rich contextual information and the variety of spatial resolutions.

VG offers significant potential for RS by allowing seamless interaction with complex geospatial imagery. It enables tasks like identifying buildings or ships from text descriptions and pinpointing areas affected by disasters or environmental changes. By addressing challenges such as handling vast datasets and improving object identification, visual grounding enhances the efficiency and accuracy of applications like urban planning, disaster response, and surveillance.

This raises a critical question: How can general visual grounding models be effectively adapted to address the unique characteristics of RS imagery while maintaining computational efficiency and achieving SOTA performance?

Visual Language Models (VLMs)[3–5] face challenges in RS due to the distinct patterns and complex spatial relationships in RS imagery. Addressing these challenges has been the focus of several SOTA approaches, which aim to bridge the gap between textual descriptions and RS imagery. GeoVG[6] introduced a fusion module that integrates geospatial relation graphs and adaptive region attention to align textual queries with RS imagery. The Multi-Granularity Visual Language Fusion (MGVLF)[7] module enhances RSVG by leveraging multi-scale features and adaptive noise filtering for better localization. LaLGA[8] innovates with a Progressive Attention (PA) module to dynamically adjust visual features at spatial and channel levels, and a Multilevel Feature Enhancement (MFE) decoder to aggregate contextual information and suppress background noise, enabling precise object identification in RS VG tasks. However, these models are generally trained from scratch, requiring extensive computational resources and making their deployment more challenging for broader applications.

This study explores the application of Parameter Efficient Fine Tuning (PEFT) techniques to adapt Grounding DINO, a visual grounding model, and OFA, a foundational vision-language model (VLM), for remote sensing tasks. Using the DIOR-RSVG[7] and OPT-RSVG[8] datasets, we evalu-

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ate the effectiveness of these techniques in addressing the computational challenges and domain-specific requirements of remote sensing, aiming to achieve competitive performance with reduced resource demands.

In this study, we make the following key contributions:

- We applied the LoRA PEFT technique to Grounding DINO, achieving a best-performing configuration that outperformed the SOTA on the DIOR-RSVG dataset.
- We compared Adapter and BitFit PEFT techniques on OFA, with Adapter showing competitive results against Visual Grounding SOTA on the DIOR-RSVG dataset.
- Using Adapter, the best-performing technique on OFA, we trained and evaluated the model on the OPT-RSVG dataset, validating its effectiveness.

## II. METHODOLOGY

### A. PEFT

In this research, we leverage Parameter-Efficient Fine Tuning (PEFT)[9] to adapt vision-language models (VLMs) for remote sensing visual grounding. PEFT fine-tunes only a minimal set of parameters, offering computational efficiency while retaining the strengths of pre-trained models.

1) *Adapter*: Adapters[10] are lightweight modules inserted between the layers of pre-trained models. They introduce a small number of additional parameters for task-specific learning while keeping most weights frozen. This makes adapters computationally efficient and effective for remote sensing visual grounding tasks, enabling the model to capture task-specific knowledge such as object localization and scale variations.

2) *Low-Rank Adaptation (LoRA)*: LoRA[11] reduces trainable parameters by applying low-rank updates to the model’s weight matrices:

$$W' = W + \Delta W, \quad \Delta W = A \cdot B,$$

where  $A \in \mathbb{R}^{d \times r}$ ,  $B \in \mathbb{R}^{r \times d}$ , and  $r \ll d$ . Here,  $W'$  is the adapted weight matrix,  $W$  is the pre-trained matrix, and  $\Delta W$  is the low-rank update. LoRA preserves original weights while learning task-specific updates, significantly reducing memory and computation requirements, making it ideal for large-scale visual grounding tasks.

3) *BitFit*: BitFit[12] fine-tunes only the bias terms of the pre-trained model’s layers:

$$W' = W + \Delta b,$$

where  $\Delta b$  represents task-specific bias adjustments. By updating only the bias terms, BitFit minimizes computational overhead while preserving the majority of pre-trained parameters, making it a highly efficient method for adapting models to specific tasks.

### B. Remote Sensing Visual Grounding datasets

Datasets play a critical role in advancing Visual Grounding in RS, yet their availability remains limited. RSVG-H[6] was the first dataset designed for this task, consisting of 4,239 RS

images, 7,933 text expressions, and 5,994 objects. While the dataset captures complex geospatial relationships, its limited size and the difficulty of precise target location constrain its applicability. DIOR-RSVG[7] expanded upon this with 17,402 images and 38,320 language expressions spanning 20 categories. However, class imbalance in DIOR-RSVG impacts model performance, often biasing predictions toward dominant classes. To address this, the OPT-RSVG[8] dataset introduced 25,452 RS images and 48,952 image-query pairs across 14 object categories, incorporating both English and Chinese annotations for broader adaptability. In this paper, we will use both the DIOR-RSVG and OPT-RSVG datasets.

### C. Evaluation Metrics

A predicted bounding box for a remote sensing (RS) image-query pair is correct if the Intersection-over-Union (IoU) with the ground-truth box exceeds a threshold, with 0.5 commonly used as a baseline accuracy metric. We report precision metrics at IoU thresholds of 0.5, 0.7, and 0.9, denoted as Pr@0.5, Pr@0.7, and Pr@0.9.

Model performance is further evaluated using mean IoU and cumulative IoU:

$$\text{meanIoU} = \frac{1}{M} \sum_t \frac{I_t}{U_t}, \quad (1)$$

$$\text{cumIoU} = \frac{\sum_t I_t}{\sum_t U_t}, \quad (2)$$

where  $t$  indexes the image-query pairs,  $M$  is the total number of pairs, and  $I_t, U_t$  are the intersection and union areas.

To assess computational efficiency, we calculate the proportion of frozen parameters:

$$\text{Efficiency} = 100 - \left( \frac{\text{Trainable Parameters (PEFT)}}{\text{Total Model Parameters}} \times 100 \right). \quad (3)$$

This metric highlights the reduced computational cost achieved through PEFT techniques by reflecting the percentage of the model that remains static during training.

### D. Model Selection

This study uses two SOTA models: OFA and Grounding DINO, chosen for their demonstrated efficacy in vision-language tasks and VG. OFA serves as a foundational model, offering a robust pre-trained architecture designed for multi-modal tasks. Its unified image-text capabilities make it highly versatile across diverse applications. Grounding DINO, on the other hand, is specifically tailored for visual grounding, leveraging cross-modal attention to accurately associate text with visual regions. Its integration into cutting-edge frameworks such as the Text Segment Anything Model (SAM)[13] underscores its versatility and effectiveness in VG tasks, positioning it as an ideal candidate for addressing remote sensing challenges.

### III. EXPERIMENTAL RESULTS

#### A. Grounding DINO

Grounding DINO is a SOTA VG model that leverages a transformer-based architecture with cross-modal attention to link text prompts to specific regions in an image. It utilizes a vision transformer (ViT) backbone for extracting rich image features and a text encoder for processing input prompts. Multi-scale deformable attention further enhances the model’s ability to integrate features from various resolutions, enabling accurate object detection and phrase localization. By adopting a unique query design, Grounding DINO achieves top-tier performance across tasks like object detection, visual grounding, and phrase localization.

In this work, Grounding DINO is divided into three distinct modules: the text encoder, the image encoder, and the decoder with integrated cross-modal attention. To enable parameter-efficient fine-tuning, we incorporated LoRA layers with a rank of 16 into all dense (fully connected) layers across these modules. This modification allows the model to adapt to the specific requirements of VG tasks while maintaining the majority of its pre-trained parameters intact. The experiments were structured to evaluate the effect of integrating LoRA into individual modules (e.g., image encoder or decoder) and combinations of modules (e.g., image encoder + decoder or all modules). These configurations were designed to identify the optimal balance between computational efficiency and task performance for VG. The variants were trained using the DIOR-RSVG training set, and their performance was evaluated on the test set. The results of this evaluation are presented in Table I.

Finally, the optimal LoRA placement configuration was evaluated against full fine-tuning and SOTA models. The comparative results, which demonstrate its efficiency and effectiveness, are presented in Table II.

Methods	Efficiency	Pr@0.5	Pr@0.7	Pr@0.9	meanIoU
Image Encoder	98.66%	54.1	47.3	27.8	48.8
Decoder	99.05%	78.1	71.5	43.2	70.0
Image Encoder + Decoder	97.70%	81.1	74.1	44.3	82.8
<b>Encoders + Decoder</b>	<b>96.74%</b>	<b>81.3</b>	<b>74.7</b>	<b>45.2</b>	<b>82.9</b>

TABLE I

PERFORMANCE METRICS FOR DIFFERENT LoRA-BASED PEFT CONFIGURATIONS APPLIED TO THE GROUNDING DINO MODEL ON THE DIOR-RSVG TEST SET. ALL NUMBERS ARE PERCENTAGES (%).

#### B. One For ALL (OFA)

The OFA (One For All) model is a Transformer-based framework for multimodal tasks like image captioning, visual question answering, and visual grounding. Its encoder-decoder architecture processes visual patches and textual tokens, learning rich joint representations through cross-attention for precise alignment. Pre-trained on large multimodal datasets, OFA generalizes well across tasks while allowing efficient fine-tuning for specialized applications, such as Remote Sensing

VG. Its unified design reduces task-specific overhead, making it a versatile and effective model for VG tasks.

To adapt the OFA model for Remote Sensing VG tasks, we employed a PEFT strategy incorporating adapters into its architecture. Most of the pre-trained parameters of the model, such as embeddings, attention mechanisms, and fully connected layers, were kept frozen to retain the extensive knowledge gained during pre-training. Task-specific learning was facilitated by introducing trainable adapter layers, specifically down-projection and up-projection modules, into both the encoder and decoder components. This integration effectively captures domain-specific features while significantly minimizing the number of trainable parameters, ensuring computational efficiency without compromising model performance.

The BitFit technique employs selective fine-tuning by freezing almost all parameters of the model, with the exception of biases. For the OFA model, the vast majority of components, including the embedding layers, convolutions, and attention mechanisms in both the encoder and decoder, were frozen. Only a small subset of parameters, mainly the biases in layer normalization, fully connected layers, and certain attention layers, were trainable. This approach reduced the number of trainable parameters to just 70,656 out of the model’s total 182 million, showcasing BitFit’s effectiveness in resource-efficient fine-tuning for domain-specific tasks.

The results of these experiment, comparing the efficiency and performance of BitFit and Adapters in fine-tuning the OFA model on DIOR-RSVG test set with SOTA models, are presented in Table II.

Methods	Pr@0.5	Pr@0.7	Pr@0.9	meanIoU	cumIoU
TransVG[14]	72.41	60.05	27.84	63.56	76.27
VLTVG (ResNet-50) [15]	69.41	58.44	24.37	59.96	71.97
VLTVG (ResNet-101)	75.79	66.33	33.11	66.32	77.85
QRNet[16]	75.84	62.27	25.69	66.80	75.39
MGVLF[7]	76.78	66.74	35.07	68.04	78.41
LaLGA[8]	<b>82.27</b>	72.25	39.55	72.35	<b>85.11</b>
Grounding DINO (Vanilla)	26.6	20.1	8.8	28.1	20.0
Grounding DINO Full Finetuning	76.8	68.4	38.1	67.5	76.3
<b>Grounding DINO + LoRA (Ours)</b>					
<b>Encoders + Decoder</b>	<b>81.3</b>	<b>74.7</b>	<b>45.2</b>	<b>82.9</b>	80.1
<b>OFA + Adapter (Ours)</b>	76.72	63.14	30.07	62.23	77.33
OFA + BitFit (Ours)	56.97	44.22	18.95	37.7	40.2

TABLE II

COMPARISON OF SOTA VISUAL GROUNDING MODELS AND OUR PROPOSED PEFT METHODS. GROUNDING DINO WITH LoRA AND OFA WITH ADAPTER AND BITFIT ON THE DIOR-RSVG TEST SET. ALL NUMBERS ARE PERCENTAGES (%).

To evaluate the generalization capabilities of parameter-efficient fine-tuning (PEFT) techniques, we conducted experiments on the English subset of the OPT-RSVG dataset. In contrast to DIOR-RSVG, which contains 20 object categories, OPT-RSVG presents unique challenges with its 14 categories, increased dataset size of 25,452 images of diverse resolutions, and greater linguistic complexity in textual expressions, averaging 10.10 words compared to DIOR-RSVG’s 7.47. Leveraging the OFA model pre-trained on DIOR-RSVG, we fine-tuned using English subset of OPT-RSVG using the Adapter PEFT

technique. These experiments underscore the adaptability and computational efficiency of PEFT methods in addressing the challenges of remote sensing visual grounding datasets with diverse characteristics and intricate textual descriptions. The comparative results with SOTA models are presented in Table III.

Methods	Pr@0.5	Pr@0.7	Pr@0.9	meanIoU	cumIoU
TransVG[14]	69.96	54.68	12.75	59.80	69.31
VLTVG (ResNet-50)[15]	71.84	57.79	14.53	61.44	70.69
VLTVG (ResNet-101)	73.50	63.11	16.31	62.48	73.86
MGVLF[7]	72.19	58.86	15.10	61.51	71.80
LaLGA[8]	74.69	60.56	15.84	63.78	74.42
<b>OFA + Adapter (Ours)</b>	<b>66.38</b>	<b>46.7</b>	<b>12.86</b>	<b>41.67</b>	<b>66.39</b>

TABLE III

COMPARISON WITH THE SOTA METHODS FOR ADAPTED OFA ON THE TEST SET OF OPT-RSVG (ENGLISH VERSION). ALL NUMBERS ARE PERCENTAGES (%)

#### IV. DISCUSSION

The results detailed in Tables I, II, and III provide an in-depth analysis of how parameter-efficient fine-tuning (PEFT) techniques were applied to adapt both the Grounding DINO and OFA models for VG tasks in RS. These results emphasize the balance between computational efficiency and performance, showcasing the effectiveness of PEFT techniques.

The performance of Grounding DINO with various LoRA placements, as shown in I, reveals interesting insights. The configuration involving both the image and decoder modules ("Encoders + Decoder") achieves the highest meanIoU of 82.9(%) and a Pr@0.9 of 45.2(%). Notably, adding the text encoder to the LoRA modules contributed minimally to performance gains, as demonstrated by the slight improvement over the "Image Encoder + Decoder" setup. This finding highlights that focusing LoRA adjustments on the image encoder and decoder is sufficient to achieve high performance. Furthermore, this setup trained only 3.26(%) of the total parameters, underscoring its computational efficiency. Compared to full fine-tuning, which updates all parameters, LoRA achieves better results while dramatically reducing resource requirements. As shown in Table II, LoRA outperformed previous state-of-the-art visual grounding models on the DIOR-RSVG dataset, achieving the highest meanIoU and competitive precision metrics. Figure 1 showcases inference results on DIOR-RSVG test set. To further demonstrate generalizability, we included results on a non-visual-grounding dataset, ISAID[17], where text prompts are arbitrary created, highlighting the versatility of the approach.

The performance comparison of OFA fine-tuning methods in Table II illustrates the potential of adapters in adapting foundation models to specialized tasks. Using adapters, OFA achieved a meanIoU of 62.23(%) with an efficiency of 99.23(%), providing a favorable trade-off between computational cost and accuracy. On the other hand, BitFit, which updates a smaller portion of parameters (0.038(%)), yielded a significantly lower meanIoU of 37.7(%). These results highlight that adapters are a more effective choice for adapting OFA to visual

grounding tasks. Furthermore, as shown in II, the adapter-based fine-tuned OFA achieves performance that is competitive with SOTA remote sensing visual grounding (RSVG) models, demonstrating its effectiveness in tackling domain-specific challenges while maintaining computational efficiency.

Moreover, the results in Table III highlight the performance of the adapted OFA model compared to state-of-the-art methods on the OPT-RSVG test set (English Version). After fine-tuning on the OPT-RSVG dataset, the adapted OFA model achieves a Pr@0.5 of 66.38(%) and a mean IoU of 41.67(%). While these results fall short of the best-performing method, LaLGA, which achieves a Pr@0.5 of 74.69(%) and a mean IoU of 63.78(%), the fine-tuned OFA model underscores the trade-offs inherent in parameter-efficient fine-tuning (PEFT). While PEFT techniques didn't achieve SOTA performance, they significantly reduce computational costs, making them viable for resource-constrained scenarios. These results reflect the challenges of adapting foundation models to highly complex datasets like OPT-RSVG, while also demonstrating the potential of PEFT methods for efficient fine-tuning.

#### V. CONCLUSION

The results collectively emphasize the effectiveness of PEFT techniques in adapting both specialized and foundation models. For Grounding DINO, LoRA demonstrates that minimal parameter updates can achieve near-SOTA performance, while OFA's use of adapters highlights the flexibility of foundation models for specialized domains. By limiting trainable parameters, PEFT techniques offer a computationally efficient and cost-effective solution for domain-specific tasks, maintaining competitive accuracy. Future work could explore hybrid PEFT approaches and more complex datasets to push the boundaries of visual grounding in remote sensing.

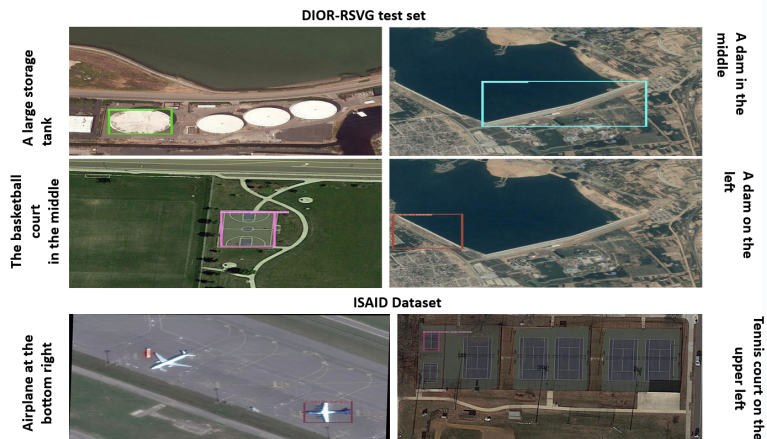


Fig. 1. Inference results of Grounding DINO adapted with LoRA PEFT on selected DIOR-RSVG test samples and ISAID dataset[17].

#### REFERENCES

- [1] S. Liu, Z. Zeng, T. Ren, F. Li, H. Zhang, J. Yang, Q. Jiang, C. Li, J. Yang, H. Su, J. Zhu, and L. Zhang, "Grounding dino: Marrying dino with grounded pre-training

- for open-set object detection,” 2024. [Online]. Available: <https://arxiv.org/abs/2303.05499>
- [2] P. Wang, A. Yang, R. Men, J. Lin, S. Bai, Z. Li, J. Ma, C. Zhou, J. Zhou, and H. Yang, “Ofa: Unifying architectures, tasks, and modalities through a simple sequence-to-sequence learning framework,” 2022. [Online]. Available: <https://arxiv.org/abs/2202.03052>
- [3] B. Xiao, H. Wu, W. Xu, X. Dai, H. Hu, Y. Lu, M. Zeng, C. Liu, and L. Yuan, “Florence-2: Advancing a unified representation for a variety of vision tasks,” 2023. [Online]. Available: <https://arxiv.org/abs/2311.06242>
- [4] J. Li, D. Li, C. Xiong, and S. Hoi, “Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation,” 2022. [Online]. Available: <https://arxiv.org/abs/2201.12086>
- [5] A. Radford, J. W. Kim, C. Hallacy, A. Ramesh, G. Goh, S. Agarwal, G. Sastry, A. Askell, P. Mishkin, J. Clark, G. Krueger, and I. Sutskever, “Learning transferable visual models from natural language supervision,” 2021. [Online]. Available: <https://arxiv.org/abs/2103.00020>
- [6] Y. Sun, S. Feng, X. Li, Y. Ye, J. Kang, and X. Huang, “Visual grounding in remote sensing images,” in *Proceedings of the 30th ACM International Conference on Multimedia*, ser. MM ’22. New York, NY, USA: Association for Computing Machinery, 2022, p. 404–412. [Online]. Available: <https://doi.org/10.1145/3503161.3548316>
- [7] Y. Zhan, Z. Xiong, and Y. Yuan, “Rsvg: Exploring data and models for visual grounding on remote sensing data,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1–13, 2023.
- [8] K. Li, D. Wang, H. Xu, H. Zhong, and C. Wang, “Language-guided progressive attention for visual grounding in remote sensing images,” *IEEE Transactions on Geoscience and Remote Sensing*, vol. 62, pp. 1–13, 2024.
- [9] Z. Han, C. Gao, J. Liu, J. Zhang, and S. Q. Zhang, “Parameter-efficient fine-tuning for large models: A comprehensive survey,” 2024. [Online]. Available: <https://arxiv.org/abs/2403.14608>
- [10] N. Houlsby, A. Giurgiu, S. Jastrzebski, B. Morrone, Q. de Laroussilhe, A. Gesmundo, M. Attariyan, and S. Gelly, “Parameter-efficient transfer learning for nlp,” 2019. [Online]. Available: <https://arxiv.org/abs/1902.00751>
- [11] E. J. Hu, Y. Shen, P. Wallis, Z. Allen-Zhu, Y. Li, S. Wang, L. Wang, and W. Chen, “Lora: Low-rank adaptation of large language models,” 2021. [Online]. Available: <https://arxiv.org/abs/2106.09685>
- [12] E. B. Zaken, S. Ravfogel, and Y. Goldberg, “Bitfit: Simple parameter-efficient fine-tuning for transformer-based masked language-models,” 2022. [Online]. Available: <https://arxiv.org/abs/2106.10199>
- [13] A. Kirillov, E. Mintun, N. Ravi, H. Mao, C. Rolland, L. Gustafson, T. Xiao, S. Whitehead, A. C. Berg, W.-Y. Lo, P. Dollár, and R. Girshick, “Segment anything,” 2023. [Online]. Available: <https://arxiv.org/abs/2304.02643>
- [14] J. Deng, Z. Yang, T. Chen, W. Zhou, and H. Li, “Transvg: End-to-end visual grounding with transformers,” 2022. [Online]. Available: <https://arxiv.org/abs/2104.08541>
- [15] L. Yang, Y. Xu, C. Yuan, W. Liu, B. Li, and W. Hu, “Improving visual grounding with visual-linguistic verification and iterative reasoning,” in *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2022, pp. 9489–9498.
- [16] J. Ye, J. Tian, M. Yan, X. Yang, X. Wang, J. Zhang, L. He, and X. Lin, “Shifting more attention to visual backbone: Query-modulated refinement networks for end-to-end visual grounding,” 2022. [Online]. Available: <https://arxiv.org/abs/2203.15442>
- [17] S. W. Zamir, A. Arora, A. Gupta, S. Khan, G. Sun, F. S. Khan, F. Zhu, L. Shao, G.-S. Xia, and X. Bai, “isaid: A large-scale dataset for instance segmentation in aerial images,” 2019. [Online]. Available: <https://arxiv.org/abs/1905.12886>