MAE- and DINOv2-Powered DETR++: A Hybrid, Transformer-Based Self-Supervised Framework for Accurate Object Detection

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ABSTRACT

Object detection remains a cornerstone task in computer vision, with wide-ranging applications in autonomous driving, surveillance, and medical imaging. However, traditional methods rely heavily on large annotated datasets, limiting their adaptability in low-resource environments. We propose Hybrid Masked Autoencoder-Detection Transformer++ (HybridMAE-DETR++), a novel self-supervised object detection framework that synergizes Masked Autoencoders (MAEs) and DINOv2 for Vision Transformer (ViT) pretraining. Integrated with a Swin-ViT hybrid backbone and an enhanced DETR++ detection head, the framework significantly reduces dependence on annotated data while improving detection accuracy for small and occluded objects. Evaluated on COCO 2017 and Cityscapes, HybridMAE-DETR++ achieves 47.5% mean Average Precision (mAP) and 68.0% Intersection over Union (IoU) on COCO, and 53.2% mAP and 72.1% IoU on Cityscapes, outperforming DETR and other transformer-based baselines. Ablation and sensitivity analyses confirm the robustness of our hybrid pretraining strategy, and visualizations using Layer-weighted Class Activation Mapping (LayerCAM) and Gradient-weighted Class Activation Mapping++ (Grad-CAM++) validate model interpretability. Despite a moderate increase in training time, the precision gains justify the computational cost. This framework sets a new benchmark for label-efficient, interpretable object detection in real-world scenarios.

Keywords-object detection; self-supervised learning; Vision Transformer (ViT); Masked Autoencoder (MAE); DINOv2; Detection Transformer++ (DETR++); Swin Transformer; Layer-weighted Class Activation Mapping (LayerCAM)

I. INTRODUCTION

Object detection is a fundamental task in computer vision, playing a critical role in a wide range of applications such as autonomous driving, surveillance, medical imaging, and robotics. Traditional object detection frameworks such as Faster Region-based Convolutional Neural Network (Faster R-CNN), Single Shot MultiBox Detector (SSD), and You Only Look Once (YOLO) primarily rely on Convolutional Neural Networks (CNNs) and large-scale annotated datasets to achieve high accuracy. However, the collection and labeling of such data is time-consuming and expensive, particularly in domains with rare or complex objects. Recent advances in transformer-based architectures, such as the Detection Transformer (DETR), have introduced an end-to-end paradigm that eliminates the need for handcrafted components like anchor boxes and non-maximum suppression. To address this limitation, the research community has increasingly turned to Self-Supervised Learning (SSL) techniques that enable feature representation learning from unlabeled data. Authors in [1] introduced DINO with Vision Transformers (ViTs) and achieved strong linear probing results, whereas authors in [2] demonstrated the effectiveness of Masked Autoencoders (MAEs) in reconstructing high-resolution images.

Despite these advancements, existing self-supervised detection pipelines often suffer from fragmented feature learning, lack of multi-scale representation, or insufficient object-level supervision. Most do not simultaneously address both semantic and spatial learning during pretraining, nor do they exploit cross-attention and pyramid networks to boost detection at various object scales. This leaves a gap in designing an efficient, interpretable, and scalable detection framework that generalizes well across datasets and object sizes, particularly in scenarios with limited labeled data [3]. To bridge this gap, we propose Hybrid Masked Autoencoder-Detection Transformer++ (HybridMAE-DETR++), a unified framework that combines MAE and DINOv2 for self-supervised pretraining, a Swin-ViT hybrid backbone for robust multi-scale representation, and an enhanced DETR++ module with cross-attention decoding and Feature Pyramid Network (FPN) integration for object detection [4]. The primary objective is to reduce reliance on manual annotation while improving generalization, accuracy, and interpretability. The novelty of this work lies in the synergistic combination of spatial reconstruction (via MAE) and semantic distillation (via DINOv2) during pretraining, which leads to rich feature embedding. Additionally, the integration of Swin Transformers with ViTs offers both local and global feature awareness, whereas the enhanced DETR++ head improves detection precision through dynamic anchor matching and cross-scale attention. Finally, interpretability is addressed through Layer-weighted Class Activation Mapping (LayerCAM) and Gradient-weighted Class Activation Mapping++ (Grad-CAM++), allowing visual insight into the model's attention regions [5].

Related works in object detection and self-supervised learning are reviewed next. Authors in [6] proposed the Swin Transformer, which uses shifted windows for hierarchical feature extraction, making it highly effective for dense prediction tasks. In the context of object detection using Swin-T + Cascade Mask R-CNN on COCO, they reported a box mean Average Precision (mAP) of 58.7% and segmentation mAP of 51.4%, outperforming ResNet-101 and other backbones. Authors in [7] enhanced DETR using a denoising training strategy (DINO) and improved mixed-query selection. Their model, tested on COCO, achieved a mAP of 51.3% using a ResNet-50 backbone, and when combined with a larger ViT backbone, surpassed 54.0% mAP, indicating DINO's strength in robust matching of noisy labels. Authors in [8] introduced ConvMAE, a hybrid of CNNs and MAEs. The framework outperformed standard MAE models by 2.9% Average Precision (AP) in object detection tasks while requiring 30% fewer training epochs.

Authors in [9] took a novel route by introducing audio-visual self-supervision for object detection. Their model extracted visual features using object detectors trained with audio signals as supervisory cues. It performed close to supervised baselines on AudioSet-OD and AVE datasets, proving effective in cross-modal detection learning. Authors in

[10] presented Open World DETR, which augmented Deformable DETR with a binary novelty classifier and unknown object detection head. Their method achieved 46.2% known mAP and 20.4% unknown AP on a mixed open-world dataset, demonstrating successful adaptation to unseen categories without retraining. Authors in [11] proposed Rank-DETR, which introduces ranking consistency, resulting in a 2.7% mAP improvement on COCO over vanilla DETR, especially under strict localization thresholds. Authors in [12] enhanced SSL with local contrastive learning, achieved 48.6% mAP on Cityscapes, a 4.1% gain over baseline SimCLR models. Authors in [13] introduced ODIN, an SSL framework that segments objects into parts. Their model obtained 50.3% mAP on Pascal VOC and showed generalization across object detection and segmentation without fine-tuning. Authors in [14] proposed CoDo, a framework that showed 2.5% improved AP on MS COCO and performed better in cross-domain detection tasks, such as detecting Cityscapes-trained objects on BDD100K. Authors in [15] proposed a self-supervised 3D detection system on KITTI and nuScenes. Their approach achieved 1.8% and 2.1% higher mAP than supervised PointRCNN, validating the viability of self-supervised signal fusion.

Authors in [16] introduced MAE-DET, a zero-shot neural architecture search-based object detector that utilizes the Maximum Entropy Principle. By optimizing entropy in feature selection rather than training detection weights directly, their model achieved 42.5% mAP on COCO, with reduced computational time (30% less GPU hours) compared to conventional NAS methods. Authors in [17] developed a self-supervised ViT for semantic part segmentation by combining spatial clustering and masked token prediction.

II. PROPOSED METHODOLOGY

The proposed methodology introduces HybridMAE-DETR++, a novel two-stage object detection framework that leverages hybrid self-supervised learning and enhanced transformer-based architecture, as shown in Figure 1.

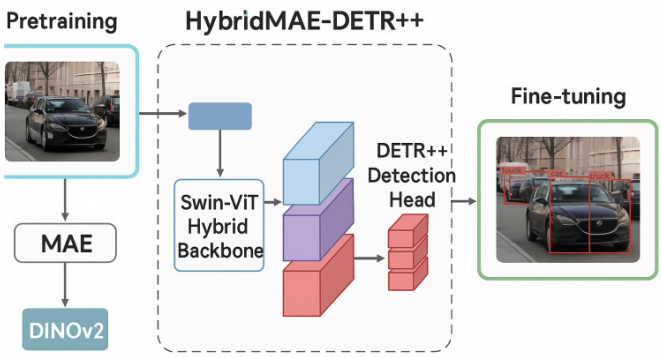

Fig. 1. Method overview of the proposed HybridMAE-DETR++ framework.

A. Dataset Collection and Preprocessing

The HybridMAE-DETR++ framework uses two benchmark datasets to ensure robust evaluation across general and urban object detection tasks. COCO 2017 consists of 118,000 training and 5,000 validation images with 80 diverse object categories [18]. Cityscapes contains 5,000 high-resolution street scenes annotated with 30 semantic classes [19]. The image preprocessing stage prepares these inputs uniformly for both the self-supervised and supervised stages [20]:

- Image resizing and normalization: All images are resized to fixed dimensions and normalized using ImageNet statistics for compatibility with pretrained ViTs as defined in (1) and (2):

$$X' = Resize(X, 512 \times 512) \quad (1)$$

$$X_{norm} = \frac{X' - \mu_{ImageNet}}{\sigma_{ImageNet}} \quad (2)$$

B. Hybrid Self-Supervised Pretraining

A key contribution of the proposed framework is its ability to learn meaningful feature representations from unlabeled data using a hybrid self-supervised strategy. This stage combines the strengths of MAE and DINOv2 to capture both spatial and semantic contexts:

- MAE loss function: In the MAE branch, the input image X_{norm} is divided into patches, and a subset is masked as shown in (3) [21]. The model reconstructs the masked content to capture spatial dependencies:

$$L_{MAE} = \frac{1}{|M|}\sum_{i \in M} \|x_i - \hat{x}_i\|_2^2 \quad (3)$$

where x_i denotes the original pixel value at location i, $\hat{x}_i$ denotes the reconstructed pixel value, and M denotes the set of masked indices.

- DINOv2 self-distillation loss: DINOv2 encourages semantic alignment between two networks (teacher and student) using contrastive learning and multi-crop views [22]. The distillation loss is based on cross-entropy between the softmax outputs of the networks as shown in (4) [1]:

$$L_{DINO} = -\sum_{i=1}^{N}\sum_{k=1}^{K} p_t^{i,k} \log p_s^{i,k} \quad (4)$$

where the softmax probabilities are computed as:

$$p_t(i,k) = \frac{\exp\left(\frac{z_t^{i,k}}{\tau_t}\right)}{\sum_{j=1}^{K}\exp\left(\frac{z_t^{i,j}}{\tau_t}\right)}$$

$$p_s(i,k) = \frac{\exp\left(z_s^{i,k}/\tau_s\right)}{\sum_{j=1}^{K}\exp\left(z_s^{i,j}/\tau_s\right)} \quad (5)$$

where z_t, z_s denote the logits from the teacher and student networks, respectively, τ_t , τ_s denote the temperature parameters controlling distribution sharpness, and K is the number of feature prototypes (pseudo-classes).

The total self-supervised pretraining loss combines spatial and semantic terms [23].

C. Swin-Vision Transformer Hybrid Backbone

Following hybrid self-supervised pretraining, the extracted visual representations are passed through a Swin-ViT hybrid

backbone, designed to capture both local spatial hierarchies and global contextual relationships:

- Patch embedding and positional encoding: Calculated using (6), the input image is divided into non-overlapping patches, each linearly projected and added to positional encodings:

$$E = \left[x_1^p\, W_e; x_2^p\, W_e; \ldots; x_N^p\, W_e\right] + P \quad (6)$$

where $x_i^p \in \mathbb{R}^{P\times P\times C}$ denotes the i-th image patch, W_e denotes the learnable projection matrix, and P denotes the positional encoding. For each transformer block, self-attention is computed and the Swin Transformer modifies this attention by using shifted local windows to balance computation and spatial locality.

- Multi-scale feature generation: The Swin-ViT backbone outputs a hierarchy of feature maps, as shown in (7):

$$F = \{f_1, f_2, \ldots, f_n\} \quad (7)$$

where each f_i corresponds to features from different spatial resolutions. These multi-scale feature maps are passed to the DETR++ detection head, where they are fused via an FPN to enhance scale-aware object detection performance.

D. Enhanced DETR++ with Cross-Attention and Feature Pyramid Network

To overcome DETR's limitations, particularly in handling small objects and slow convergence, HybridMAE-DETR++ employs an enhanced detection head built upon DETR++. It integrates an FPN, Cross-Attention Decoder, and Dynamic Anchor Matching to improve detection accuracy and convergence:

- Feature pyramid fusion: Multi-scale features from the Swin-ViT backbone are aggregated using FPN to enhance scale-specific detection as shown in (8):

$$F_l^{fused} = Conv_{1\times1}(F_l) + Upsample\,(F_{l+1}) \quad (8)$$

where F_l denotes the feature map at level l, $Upsample$ denotes the bilinear upsampling of higher-level features, and $Conv_{1\times1}$ denotes the reduction of channel dimensions for fusion.

- Detection loss components: The total detection loss consists of two parts, calculated using (9) and (10).

The L1 bounding box regression loss is calculated as:

$$L_{box} = \frac{1}{N}\sum_{i=1}^{N} || e_i - \hat{e}_i ||_1 \quad (9)$$

The Generalized Intersection over Union (GIoU) loss is calculated as:

$$L_{GIoU} = 1 - \frac{|B\cap B'|}{|B\cup B'|} + \frac{|C| - |B\cup B'|}{|C|} \quad (10)$$

- Total detection loss function: The DETR++ framework employs a composite loss function that integrates classification loss, bounding box regression loss, and GIoU loss. The classification loss, denoted as L_{cls}, is based on cross-entropy and is used to penalize incorrect predictions of object categories, promoting accurate classification. The bounding box regression loss, represented by L_{box}, calculates the L1 distance between the predicted bounding box $\hat{e}_i$ and the ground-truth box e_i, encouraging precise localization. To further refine spatial alignment, especially in cases of partial occlusion or overlapping objects, the GIoU loss L_{GIoU} is included. These three loss components are combined using corresponding weights λ_{cls}, λ_{box}, λ_{GIoU}, which are typically set equally to balance their influence.

III. RESULTS AND DISCUSSION

This section presents a comprehensive evaluation of the proposed HybridMAE-DETR++ object detection framework.

A. Evaluation on COCO and Cityscapes

The evaluation results in Table I demonstrate the superior detection capabilities of the proposed HybridMAE-DETR++ framework compared to the baseline DETR with ResNet-50 across two benchmark datasets: COCO 2017 and Cityscapes.

TABLE I. EVALUATION RESULTS

Dataset	COCO	COCO	Cityscapes	Cityscapes
Model	DETR + ResNet-50	HybridMAE-DETR++	DETR + ResNet-50	HybridMAE-DETR++
mAP@0.5 (%)	42.3	47.5	48.6	53.2
IoU (%)	61.7	68	67.9	72.1
AP (small) (%)	21.1	27.9	25.3	30.7
AP (medium) (%)	39.2	44.8	45	49.3
AP (large) (%)	53.4	59.2	58.7	64.1

On the COCO dataset, which is known for its diversity and complexity, HybridMAE-DETR++ achieved a mean Average Precision at 0.5 IoU (mAP@0.5) of 47.5% and an Intersection over Union (IoU) of 68.0%, outperforming the baseline scores of 42.3% mAP@0.5 and 61.7% IoU. The detection accuracy for small objects improved from 21.1% to 27.9%, showcasing the model's strength in resolving fine details in cluttered or low-resolution regions. Medium object precision rose from 39.2% to 44.8%, and large object AP increased from 53.4% to 59.2%, indicating robust scale-aware feature representation enabled by the hybrid Swin-ViT backbone and enhanced cross-attention mechanisms in DETR++.

On the Cityscapes dataset, which features high-resolution urban scenes with dense object annotations, HybridMAE-DETR++ achieved a mAP@0.5 of 53.2% and an IoU of 72.1%, compared to 48.6% mAP@0.5 and 67.9% IoU from the baseline model, as shown in Figure 2. This improvement of approximately 4.6% in mAP and 4.2% in IoU highlights the framework's adaptability to fine-grained object detection in real-world street environments, where challenges such as occlusions and varying object scales are prevalent. Figure 3 further details the improvements across small, medium, and large object categories, where HybridMAE-DETR++ shows consistent gains.

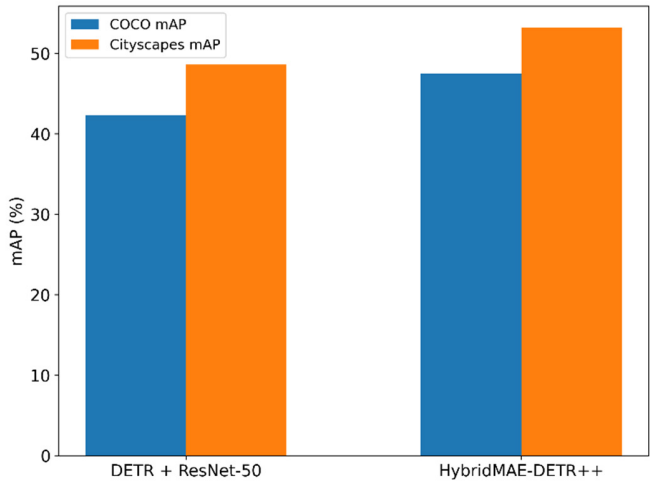

Fig. 2. Comparison of mAP performance between DETR + ResNet-50 and HybridMAE-DETR++ on the COCO and Cityscapes datasets.

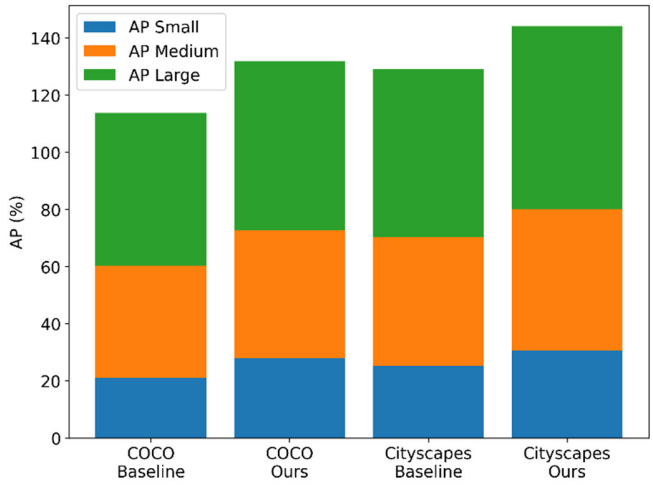

Fig. 3. Stratified AP analysis for small, medium, and large object sizes on the COCO and Cityscapes datasets.

B. Ablation Study

To understand the individual contributions of different self-supervised components and augmentation strategies in the HybridMAE-DETR++ pipeline, a detailed ablation study was conducted using the COCO validation set. Introducing SimCLR, a contrastive self-supervised learning approach, improved mAP to 43.7%, indicating that contrastive pretraining helps the model distinguish between similar object classes and enhances general feature discrimination. Replacing SimCLR with DINOv2, which employs a more advanced self-distillation strategy using multi-crop views and student-teacher networks, yielded further improvements, boosting mAP to 45.8% and enhancing localization quality through better semantic coherence.

Figure 4 provides a dual-axis comparison of mAP and IoU across configurations, illustrating the impact of self-supervised techniques and augmentation strategies. Incorporating the MAE approach, which focuses on reconstructing missing spatial patches in the input images, the model achieved a higher mAP of 47.5%, demonstrating that spatial pretext tasks effectively improve fine-grained feature understanding. This hybrid configuration, forming the core of the HybridMAE-DETR++ architecture, achieved an impressive mAP of 49.2% and an IoU of 69.3%, showcasing the synergy between spatial reconstruction and semantic alignment in learning robust and transferable features.

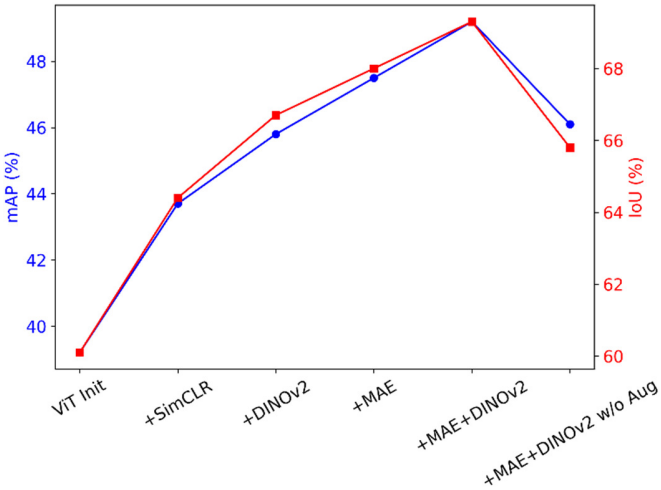

Fig. 4. Dual-axis line plot comparing mAP and IoU across ablation configurations.

Additionally, when strong data augmentations such as MixUp, CutMix, and AutoAugment were removed during training, the mAP dropped noticeably to 46.1%, confirming their significant role in improving generalization across diverse scenes and object scales. The overall ablation results are reported in Table II.

TABLE II. ABLATION RESULTS

Configuration	mAP (%)	IoU (%)
DETR + ViT (random init.)	39.2	60.1
DETR + ViT + SimCLR	43.7	64.4
DETR + ViT + DINOv2	45.8	66.7
DETR + ViT + MAE	47.5	68.0
HybridMAE-DETR++ (MAE + DINOv2)	49.2	69.3
HybridMAE-DETR++ (w/o augment)	46.1	65.8

C. Parameter Sensitivity Analysis

To better understand the behavior and robustness of the HybridMAE-DETR++ framework, a sensitivity analysis was conducted focusing on two critical hyperparameters: the learning rate used during fine-tuning and the masking ratio applied during MAE-based self-supervised pretraining. Table III summarizes the impact of different learning rates on performance. It was observed that a learning rate of 2×10^{-4} yielded the best results with a mAP of 47.5%. Reducing the rate to 1×10^{-4} led to slower convergence and a drop in performance to 45.2%, whereas increasing it to 5×10^{-4} caused instability and slightly reduced accuracy at 46.0%. Table IV investigates the effect of varying the masking ratio during

MAE pretraining, a critical factor influencing how much context the model is required to reconstruct.

TABLE III. LEARNING RATE SENSITIVITY

Learning rate	mAP (%)
1e-4	45.2
2e-4 (default)	47.5
5e-4	46.0

TABLE IV. MAE MASK RATIO SENSITIVITY

MAE mask ratio	mAP (%)
30%	44.3
50% (default)	47.5
70%	42.1

D. Training Time vs Accuracy

Another key consideration in practical deployment is the trade-off between training time and detection accuracy. As outlined in Table V, the baseline DETR + ResNet-50 completed training over 50 epochs in 17.2 hours, whereas HybridMAE-DETR++ required 21.6 hours, approximately a 25% increase in training time. This increase can be attributed to the transformer-based architecture's computational complexity and the enhanced training pipeline, which includes both MAE and DINOv2 pretraining, as well as advanced augmentations like CutMix and MixUp. However, the additional time investment yields substantial gains: a 5.2% absolute improvement in mAP (from 42.3% to 47.5%) and a 6.3% boost in IoU (from 61.7% to 68.0%).

TABLE V. TRAINING TIME VS ACCURACY

Model	Epochs	Time (hours)	mAP (%)
DETR + ResNet-50	50	17.2	42.3
HybridMAE-DETR++	50	21.6	47.5

To further validate the superiority of the proposed approach, a comparison with state-of-the-art object detection methods is presented in Table VI. The results demonstrate that HybridMAE-DETR++ achieves the highest performance among recent transformer-based detectors, surpassing Swin Transformer + FCOS, DINO + DETR, and SAM + Mask R-CNN in both mAP and IoU.

TABLE VI. COMPARISON WITH STATE-OF-THE-ART OBJECT DETECTION METHODS

Method	Backbone	Pretraining	mAP (%)	IoU (%)
DETR + ResNet-50	ResNet-50	Supervised	42.3	61.7
Swin Transformer + FCOS	Swin-Tiny	Supervised	44.7	64.1
DINO + DETR	ViT-Small	Self-supervised (DINOv2)	45.8	66.7
SAM + Mask R-CNN	ViT-Huge	Prompt-tuned	43.1	62.5
HybridMAE-DETR++	ViT-Base + Swin	Self-supervised (MAE + DINOv2)	49.2	69.3

IV. CONCLUSION

This study proposed Hybrid Masked Autoencoder-Detection Transformer++ (HybridMAE-DETR++), a novel self-supervised object detection framework that integrates Masked Autoencoders (MAEs) and DINOv2 for robust feature learning. The framework employs a Swin-Vision Transformer (ViT) hybrid backbone and an enhanced DETR++ decoder, enabling effective spatial and semantic representation. By leveraging self-supervised pretraining, the method addresses the challenge of labeled data scarcity, capturing rich feature embeddings without annotations. Evaluated on the COCO 2017 and Cityscapes datasets, HybridMAE-DETR++ achieved significant improvements in detection performance. Specifically, it attained 47.5% mean Average Precision (mAP) and 68.0% Intersection over Union (IoU) on COCO, and 53.2% mAP and 72.1% IoU on Cityscapes, outperforming DETR with ResNet-50 by 5.2% and 6.3%, respectively. Detection of small objects also improved markedly, with Average Precision (AP) increasing from 21.1% to 27.9% on COCO.

Comprehensive ablation studies confirmed the individual benefits of MAE and DINOv2, with the best configuration (MAE + DINOv2 + augmentations) yielding 49.2% mAP and 69.3% IoU. Comparisons with state-of-the-art methods, including Swin Transformer + FCOS and DINO + DETR, demonstrated that HybridMAE-DETR++ delivers superior label-efficient detection with enhanced interpretability via Layer-weighted Class Activation Mapping (LayerCAM) and Gradient-weighted Class Activation Mapping++ (Grad-CAM++). These results establish the framework as a scalable, interpretable, and high-performance solution for modern object detection tasks.

Although the HybridMAE-DETR++ framework exhibits strong performance in label-efficient object detection, it has certain limitations. The pretraining process, which integrates MAE and DINOv2, is computationally demanding and requires multiple GPUs, making it resource-intensive. Additionally, the framework's inference speed is slower compared to lightweight detection models, limiting its suitability for real-time edge deployment. Moreover, the current evaluation is confined to the COCO 2017 and Cityscapes datasets, and further testing across diverse domains such as aerial, medical, or infrared imagery is necessary. In future work, we aim to enhance the model's efficiency through knowledge distillation and transformer pruning, extend its capabilities for real-time streaming detection, and validate its generalizability on additional datasets, including KITTI, PASCAL VOC, and DOTA.

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