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# Research on Deep Semi-Supervised Object Detection Based on Active Learning

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## ABSTRACT

As a key paradigm connecting supervised learning and unsupervised learning, deep semi-supervised object detection technology aims to enhance the generalization ability and training efficiency of models in real-world scenarios where labeled data is scarce. This method effectively alleviates the dependency of traditional fully supervised models on intensive manual annotation by synergistically utilizing a small number of high- quality labeled samples and large-scale unlabeled data. It particularly demonstrates significant advantages in high-cost annotation fields such as remote sensing image analysis, medical image diagnosis, and autonomous driving perception. Experimental verification shows that the collaborative architecture integrating active sampling and semi-supervised learning achieves performance breakthroughs on multiple datasets, including Pascal VOC, MS-COCO, as well as specialized datasets such as remote sensing and underwater sonar. It not only significantly reduces annotation costs but also exhibits good adaptability in challenging scenarios such as domain shift, class imbalance, and small object detection.

## KEYWORDS

Semi-supervised learning; Object detection; Active learning; Deep learning; Model Generalization

## 1. THEORETICAL BASIS AND METHODOLOGICAL SYSTEM OF DEEP SEMI-SUPERVISED OBJECT DETECTION

### 1.1. Basic Principles and Advantages of Semi-Supervised Learning in Object Detection

Semi-supervised learning, as a key paradigm connecting supervised learning and unsupervised learning, its core mechanism lies in the collaborative utilization of a small number of high-quality labeled samples and large-scale unlabeled data, to alleviate the strong dependence of deep object detection models on dense pixel-level bounding box annotations. [1] In practical industrial scenarios, such as remote sensing image analysis, medical image lesion localization, and multi-object perception for autonomous driving, manually annotating a target instance takes an average of 3.2–5.7 minutes and is prone to the subjective bias of the annotator, resulting in annotation consistency often below 0.68. This makes fully supervised training face fundamental bottlenecks in terms of cost and scalability. In contrast, semi-supervised learning constructs a closed-loop mechanism of pseudo-label generation-screening-feedback, mining structured prior information from unlabeled samples in the feature space, such as the long-tail characteristic of target scale distribution, the anisotropic distribution of bounding box regression residuals, and the manifold continuity of semantic boundaries between categories. Thus, without increasing the burden of manual annotation, it significantly enhances the model's robustness to occlusion, small targets, and domain shift scenarios. [2] It is worth

noting that the improvement in generalization ability of semi-supervised object detection does not stem from the simple accumulation of data volume, but rather from implicitly regularizing the intermediate layer features ofthe backbone network through the contextual correlation and geometric invariance contained in unlabeled data, thereby mitigating the risk of overfitting and enhancing feature decoupling ability. This mechanism is particularly crucial in small sample settings, where limited annotations struggle to cover the complete distribution of target poses, illumination, and occlusion. The semi-supervised framework can strengthen the compactness of features for similar targets through an unsupervised contrastive learning module, ultimately achieving an absolute improvement of 6.9% on the PASCAL VOC benchmark, validating its structural advantage under scarce annotation conditions [3].

### 1.2. Synergistic Mechanism Between Active Learning and Semi-Supervised Learning

The collaborative mechanism between active learning and semi-supervised learning is not a simple concatenation of the two in the training process, but a closed-loop feedback structure formed at three key stages: sample selection, pseudo-label generation, and model updating. [4] The core of this mechanism lies in: active learning predicts the confidence distribution and geometric characteristics ofthe feature space boundary through modeling, and performs uncertainty sampling and diversity sampling on the unlabeled dataset, thereby selecting candidate sample subsets with the highest information entropy and the most ambiguous class discriminative boundaries; these samples, after manual verification to obtain high-quality true labels, are systematically injected into the annotation pool ofthe semi-supervised learning framework to correct the semantic drift caused by distribution shift or model overfitting in the pseudo-label generator. [5] It is worth noting that in object detection tasks, this collaboration needs to further incorporate localization accuracy constraints - for example, using IoU threshold-based bounding box confidence weighted uncertainty metrics, rather than relying solely on the probability entropy output by the classification branch, to avoid polluting the supervision signal with high-confidence but significantly mislocated false positive samples. Furthermore, when dealing with long-tail distribution scenarios, the collaborative mechanism leverages the sensitivity of active learning (AL) to minority class instances, preferentially selecting heavily occluded, extremely small-scale, or abnormally-posed target candidate boxes into the annotation queue, thereby alleviating the class bias problem caused by the dominance of majority classes in semi-supervised learning (SSL). Moreover, when facing novel attack patterns or unknown class targets, this mechanism can identify outlier samples far from existing annotation clusters in the feature embedding space through a clustering-guided constraint propagation strategy, and incorporate them into the active query queue, providing an extensible incremental learning paradigm for open-world object detection. In summary, the deep coupling of active learning and semi-supervised learning essentially constructs a dual-driven learning architecture that is constrained by annotation efficiency, targets model robustness, and optimizes semantic consistency. Its theoretical effectiveness has been fully validated on the Caltech pedestrian detection dataset and the ILSVRC detection benchmark, while the introduction of the SimOTA global optimal allocation strategy and noise-aware loss function further enhances the generalization ability of this architecture in complex occlusion and multi-scale scenarios [6].

## 2. KEY TECHNOLOGIES FOR DEEP SEMI-SUPERVISED OBJECT DETECTION BASED ON ACTIVE LEARNING

### 2.1. Active Sample Selection And Query Strategy Design

Active sample selection and query strategy design are core components in deep semi- supervised object detection frameworks, aiming to achieve synergistic optimization of annotation efficiency and

model generalization ability. Their essence lies in constructing a task-specific, differentiable, or sortable sample uncertainty measurement mechanism, and guiding annotation resources towards difficult regions with maximum information gain based on this. Compared to traditional classification tasks, the sample space in object detection scenarios exhibits significant structural heterogeneity: within a single image, there are multi-scale target instances, densely overlapping bounding boxes, local regions with ambiguous class semantics, and feature degradation phenomena caused by occlusion, low resolution, or motion blur. [7] This makes it difficult for naive sampling strategies based on a single confidence threshold or global entropy value to effectively identify truly discriminative candidate samples. To address this, current research is gradually shifting towards composite query paradigms that integrate multi-dimensional geometric and statistical characteristics. To alleviate this problem, a clustering structure-guided active learning mechanism has been introduced into the object detection process. The core idea is to embed the deep features of unlabeled images into a low-dimensional manifold space. Under the constraints of maintaining intra-class compactness and inter-class separability, samples across cluster boundaries with low neighborhood label consistency are preferentially selected for manual verification. This approach reduces annotation redundancy while enhancing the model's ability to model the spatial relationships of occluded targets [8].

The effectiveness of such methods is highly dependent on the discriminability of feature representation. When the target scale difference exceeds two orders of magnitude or there is severe intra-class appearance variation, relying solely on Euclidean distance- based K-means clustering can easily lead to distorted cluster structures. [9] To address this limitation, recent research has further coupled entropy measurement with contrastive learning mechanisms to construct pixel-level uncertainty heatmaps. It enhances global context modeling through an entropy-based segmentation loss function and dynamically adjusts the confidence weights ofpseudo-labels in different spatial regions with the help of an uncertainty weighting mechanism. This design achieves an average absolute error of 7.89 and a detection accuracy of 94.69% in the task of detecting salient targets in side-scan sonar underwater images, verifying the robustness ofthe uncertainty-aware strategy under complex background interference. Additionally, multi-model divergence strategies are also used to alleviate sampling bias caused by single-model deviations. [10] Typical implementations include integrating multiple structurally heterogeneous detectors and calculating joint indicators such as bounding box IoU divergence and classification logits KL divergence. In summary, the active query strategy for target detection tasks has evolved from a single uncertainty measurement to a multi-granularity collaborative selection paradigm that integrates geometric structure, statistical characteristics, and semantic consistency. Its effectiveness in difficult case identification is not only reflected in the improvement of quantitative indicators but also in the enhanced adaptability of the model to long-tail distributions, weak supervision signals, and dynamic environmental perturbations [11].

## 2.2. Pseudo-label Generation And Quality Control Mechanism

Pseudo-label generation serves as a crucial bridge connecting supervised signals with unlabeled data in deep semi-supervised object detection. Its reliability directly determines the convergence stability and upper bound ofthe model's generalization ability. [12] In practical deployment scenarios, especially in closed-circuit television surveillance systems, due to significant distribution shifts between the training domain and the real deployment domain, coupled with strict restrictions on original labeled data imposed by privacy regulations, incorporating pseudo-labels into the training loop without strict quality control can easily lead to error accumulation and class drift, thereby causing a steep decline in model performance. Among the current mainstream frameworks, self-training remains the preferred paradigm in the industry due to its simplicity and engineering interpretability. Its core mechanism lies in utilizing a teacher model to assign pseudo-labels to high-confidence prediction samples, and injecting them into the loss function of the student model in a

weighted manner, thereby achieving dynamic expansion of the training set. However, the inherent one-way knowledge distillation characteristic of this paradigm makes it highly sensitive to initial model biases and lacks explicit modeling of the consistency of the prediction space structure. Consistency regularization approaches from the perspective of perturbation invariance, forcing the model to output semantically consistent bounding box regression parameters and classification logits under weak and strong augmentation views, constituting dual constraints on the geometric rationality and semantic coherence of pseudo-labels [13].

To further overcome the passive limitations of traditional threshold truncation strategies, recent research has shifted towards a more proactive quality control paradigm. For instance, the Dense Information Learning (DIL) framework abandons the static filtering logic that relies solely on the original information of single-frame images. [14] Instead, it constructs a foreground bank to aggregate discriminative instance features across samples and scales, and utilizes the Dense Information Augmentation (DIA) module to encode prior knowledge as controllable perturbations, actively injecting structured semantic information into unlabeled images while simultaneously filtering noise and enriching information. On this basis, a relational consistency constraint is proposed to compensate for the lack of modeling topological relationships between categories in existing methods: this mechanism not only requires the same instance to maintain prediction consistency under different perturbations, but also forces the network to maintain relative distance relationships between classes at the feature manifold level, thereby suppressing false label misclassifications caused by category confusion. Experiments show that when only 5% and 10% of the MS-COCO dataset is used, DIL improves the mAP by 12.6 and 10.0 percentage points respectively compared to the fully supervised baseline. Furthermore, in scenarios with strong domain shifts such as Cityscapes→Foggy Cityscapes, the improved Mean Teacher framework, which integrates pseudo-label fusion, Static Adversarial Regularization (SAR), and time-decay weighting strategies, still achieves an average mAP@0.5 improvement of7.2 under low label settings, validating the effectiveness of a multi-dimensional quality control mechanism in mitigating the dual challenges of domain shift and scarce labeling. It is worth noting that the aforementioned technical paths are not isolated from each other, and their synergistic effectiveness relies on the systematic design and joint optimization of confidence measurement mechanisms, stopping criteria, and evaluation metrics.

# 3. TYPICAL ALGORITHM PERFORMANCE EVALUATION AND DATASET ADAPTATION ANALYSIS

## 3.1. Experimental Verification on Mainstream Benchmark Datasets

In the experimental verification phase on mainstream benchmark datasets, this study systematically evaluated the generalization ability and robustness of the active learning and semi-supervised learning collaborative paradigm and its representative derivative methods in multi-source heterogeneous visual scenes. The experiments covered the general object detection benchmarks Pascal VOC and MS-COCO. The latter, due to its inclusion of 80 fine-grained object classes, highly imbalanced instance distribution, and complex background interference, is widely regarded as a rigorous platform for testing the adaptability of models to small objects, occlusion, and scale variations. The pedestrian detection dataset, characterized by high density, low resolution, severe deformation, and abrupt illumination changes, constitutes a typical challenging scenario under the dual constraints of false positive rate and false negative rate in pedestrian detection tasks. On this dataset, the ASDL framework compressed the false negative rate to 12.2%,significantly outperforming the state-of-the-art (SOTA) methods at the same time. The ILSVRC detection task, with its million-scale image size and cross-domain semantic transfer requirements, provided key support for verifying the convergence stability of algorithms under large-scale weakly supervised conditions. It is worth noting that the specialized evaluation for remote sensing images revealed the deep constraints of class long-tail distribution and spatial semantic sparsity on the quality ofpseudo-labels. Existing semi-supervised

methods often suffer from a cliff-like drop in mAP50-95 on remote sensing data due to insufficient recall of tail classes. However, after introducing the triple exponential moving average teacher-student architecture and a two-stage class adaptation module, the framework achieved breakthrough metrics of mAP50=75.8 and mAP50- 95=51.5 on the remote sensing dataset, with no typical false positives or boundary blurring phenomena observed in the visual detection results.

For the extreme modality of underwater sonar images, the EUCL method achieves a performance of MAE=7.89 and Acc=94.69 on a side-scan sonar dataset by constructing a contrastive learning mechanism based on entropy uncertainty. Its uncertainty-weighted strategy effectively mitigates the pseudo-label drift problem caused by water reverberation noise and the confusion of target-background acoustic features. Furthermore, in privacy- sensitive closed-circuit television deployment scenarios, the source-free domain adaptation framework improves mAP@0.5 by 5.4 percentage points in strong domain shift tasks such as Cityscapes→Foggy Cityscapes through static adversarial regularization and dynamic time-weighted pseudo-label fusion strategies, and maintains a 6.8-point gain even with only 2 labeled samples in an extremely low-resource setting, demonstrating its domain-invariant representation transfer ability under data-invisibility conditions. The DIL method takes a different approach by actively constructing unlabeled samples rich in discriminative foreground semantics through dense information enhancement, and combines relational consistency regularization to force the network to maintain cross- perturbation invariance at the feature manifold level. It achieves a 12.6-point mAP improvement over the supervised baseline on MS-COCO with only 5% labeled data. The aforementioned multi-dimensional empirical evidence indicates that the underlying statistical characteristics of different datasets profoundly affect the optimal configuration of active sampling strategies, pseudo-label filtering thresholds, and consistency regularization strengths. A single general paradigm cannot accommodate all scenarios, and there is an urgent need to establish an adaptive evaluation protocol driven by task priors.

### 3.2. Generalization Ability And Challenges in Cross-Domain Scenarios

The generalization ability and challenges in cross-domain scenarios essentially stem from multiple coupled mismatches encountered by deep semi-supervised object detection models under out-of-distribution conditions: these include both low-level feature space shifts induced by imaging modality differences and high-level semantic modeling biases caused by task prior imbalances. In the practical deployment of CCTV surveillance systems, models often face significant domain gaps, typically manifested as systematic inconsistencies between synthetic data used during training and real surveillance videos in terms of lighting conditions, motion blur, lens distortion, and low resolution characteristics. Furthermore, the increasingly stringent Personal Information Protection Law and data localization policies further restrict the migration and re-annotation of source domain data, forcing algorithms to adapt to the target domain under source-free constraints. Remote sensing image object detection exhibits extreme class imbalance characteristics—in a long-tail distribution, the sample size of sparse classes such as small-sized ships and isolated power towers may be less than one-thousandth of the dominant class, leading to a severe bias towards high-frequency classes in the pseudo-label generation process and persistently low recall rates for tail classes. To address this, recent research has constructed a triple exponential sliding average teacher-student network architecture, supplemented by a two-stage class adaptation module, which improved mAP50-95 to 51.5 on the DOTA- v1.5 dataset, validating the crucial role of explicit class balancing mechanisms in enhancing the robustness of the semi-supervised paradigm. Underwater sonar image detection faces more complex physical layer challenges: side-scan sonar imaging is affected by multipath reflection, sound wave attenuation, and sediment scattering, resulting in blurred target boundaries, extremely low signal-to-noise ratio, and highly non- stationary background textures. Although existing methods introduce the Entropy Uncertainty Contrastive Learning (EUCL) framework, which utilizes uncertainty map weighting and contextual contrastive loss to jointly optimize pseudo-label quality, significant false detections still occur in strong reverberation interference areas. The performance

metric of Mean Absolute Error (MAE) at 7.89 reflects the fundamental constraints imposed by the inherent physical limitations of acoustic imaging on deep representation learning.

Furthermore, in scenes with dense small targets, the semantic gap and localization regression bias of the feature pyramid are further amplified. Traditional single-stage detectors, lacking a refined feature alignment mechanism, struggle to maintain sufficient discriminative response at the pixel level. The aforementioned four typical cross-domain challenges collectively reveal that domain shift intensity, annotation scarcity, class distribution skewness, and physical imaging degradation effects are not independent variables but are coupled in a nonlinear manner, influencing the convergence trajectory and generalization boundary of semi-supervised learning. There is an urgent need to construct a novel collaborative optimization framework that combines domain-invariant representation decoupling capabilities, class-aware pseudo-label calibration mechanisms, and regularization strategies guided by physical models.

# 4. APPLICATION EXPANSION AND DEVELOPMENT TRENDS

## 4.1. Implementation Path Tailored To Real-World Engineering Scenarios

The implementation path tailored for real-world engineering scenarios must balance the triple constraints of algorithm performance, annotation efficiency, and hardware adaptability. Its core value lies in transforming the active learning-driven deep semi- supervised object detection paradigm from a theoretical model into a deployable, iterable, and scalable industrial-grade solution. In the vine trunk semantic segmentation task, researchers used only 300 manually fine-labeled images as a seed set to construct a self- training closed loop through consistency regularization and a pseudo-label confidence threshold filtering mechanism. This ultimately generated a high-quality pixel-level annotated dataset with a scale of 35,000 frames, compressing the manual annotation time to 1% ofthe traditional fully supervised process, significantly alleviating the long-standing "annotation cold start" bottleneck in the field of agricultural robots. This path not only reduces data acquisition costs but also achieves a Pareto optimality of 81% validation accuracy and 5ms single-frame inference latency through a lightweight UNet variant. It completes end-to-end real-time segmentation inference on a mobile robot platform equipped with Jetson AGX Orin, meeting the millisecond-level response requirements for structured light perception-semantic localization-trajectory planning in vineyard suckering operations.

In the field of network security, a semi-supervised clustering framework is embedded into an intrusion detection system. Through active learning strategies, unlabeled network flow samples with the highest information entropy are dynamically selected and submitted for expert annotation. By combining pairwise constraints to guide spectral clustering and optimizing the objective function, a small number of labeled samples (<0.5%) can calibrate the intra-cluster compactness and inter-cluster separability. For ambiguous clustering areas, an improved K-nearest neighbor classifier based on local density weighting is introduced to effectively identify zero-day attack variants, reducing the false alarm rate by 37.2% compared to traditional DBSCAN. enter

In the deployment of intelligent security edge devices, the collaborative design of model compression technology and online tracking module has reduced the parameter count of the YOLOv5s backbone network by 62.4%, while maintaining an mAP@0.5 of 76.3%. The measured power consumption on the RK3588 platform is stably controlled within 3.8W. The above case collectively demonstrates that the active semi-supervised paradigm is not merely an improvement in algorithms, but rather reconstructs the engineering closed loop of "data collection - model training - edge deployment - feedback iteration". Its essence lies in seeking a dynamic equilibrium point between annotation cost, accuracy loss, and inference overhead through a human-machine collaborative annotation mechanism and resource-aware model architecture design.

### 4.2. Future Research Directions And Technological Evolution Trends

Future research directions and technological evolution trends are undergoing a profound shift from being driven by a single paradigm to evolving in a multi-dimensional collaborative manner. In terms of dynamic annotation budget allocation, existing active learning strategies often rely on static confidence thresholds or uncertainty sampling mechanisms, making them difficult to adapt to complex scenarios such as class distribution shifts, long-tail characteristics, and the coupling of localization regression errors in object detection tasks. There is an urgent need to construct an online budget-aware scheduling framework driven by meta-learning, enabling adaptive reallocation of annotation resources between classification branches and regression heads. Multimodal active sampling breaks through the limitations of traditional methods that rely solely on RGB image features, integrating complementary representations from heterogeneous modalities such as infrared, depth, and event cameras. Through a cross-modal attention gating mechanism, the most informative unannotated samples are selected. This approach has demonstrated significant improvements in robustness to occlusion and low illumination in remote sensing and autonomous driving scenarios. The interpretable pseudo-label verification mechanism is gradually replacing black-box consistency regularization. By utilizing gradient-like activation mapping and detection box semantic consistency verification modules, fine- grained credibility assessment is performed on pseudo-labels generated by the teacher model, thereby suppressing error propagation. This method has improved the semi-supervised mAP by 3.7 percentage points on the PASCAL VOC benchmark. It is particularly noteworthy that the collaborative learning paradigm with large models is giving rise to new hybrid training protocols: visual-language large models (such as CLIP- ViT) are used as unsupervised semantic prior extractors, and their frozen text-image alignment embedding spaces provide cross-modal semantic anchors for unannotated images, guiding the weakly supervised initialization of the region proposal network. This idea has been validated for its effectiveness in the MS-COCO few-shot transfer task.

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