Stream-Based Active Distillation for scalable model deployment

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Abstract

This paper proposes a scalable technique for developing lightweight yet powerful models for object detection in videos using self-training with knowledge distillation. This approach involves training a compact student model using pseudo-labels generated by a large and powerful teacher model, which can help to reduce the need for massive amounts of data and computational power. However, model-based annotations in large-scale applications may propagate errors or biases, and incur high costs. To address these issues, the paper introduces Stream-Based Active Distillation (SBAD) to endow students with effective, query-efficient methods that are robust to teacher imperfections. The proposed pipeline considers on-the-fly decision-making to query or not an image from a video to avoid storing data. Simple yet effective strategies are compared, demonstrating 1) the effectiveness of distillation for low annotation budget and 2) the importance of querying images with the highest confidence.

1. Introduction

Deep Neural Networks (DNNs) are effective for object detection in images, but their predictive power comes at a high cost. The training of highly performant DNNs requires high-performance cloud servers with a large-scale dataset which requires (i) a large workforce to prepare the dataset or training implementation (ii) as well as a significant investment of time and money. These data, time, and hardware costs create a barrier for most practitioners in terms of going from theory to practice [5]. Furthermore, a one-shot investment in resources to create large general-purpose models, regardless of their size, is no longer sufficient. With no retraining, these models cannot be robust with respect to **stochastic** and **ever-evolving** environments. In the example of Closed-Circuit Television (CCTV) monitoring traffic at city-scale, there is no dataset large enough to cover all aspects of every urban landscape [33]. Therefore, a *scalable, efficient, and recurrent* retraining is necessary to reduce costs and avoid **under-performing** systems.

Knowledge Distillation (KD) is a promising technique that enables the creation of lightweight, yet powerful models. The process assumes that for the same dataset, large models (i.e, *teachers*) have higher knowledge capacity than smaller models (i.e., *students)*. The teacher, typically a pre-trained or very large generic model (e.g., YOLOv8x6), can transfer its knowledge (i.e., pattern recognition mechanisms) to students without significant model degradation. However, the recourse to other models for labelling could lead to confirmation bias, a phenomenon referring to the noise accumulation when the model is trained using incorrect predictions for semi-supervised or unsupervised learning [2]. Furthermore, an immediate rebound effect of the scheme is the multiplication, at scale, of the number of models to be trained. The inference costs could become significant. Additionally, if the teacher model is running on a cloud-based platform, there may be additional costs associated with its usage, such as hourly usage fees or data transfer costs. This could be mitigated by using Active Learning (AL), which aims to identify the most informative examples for labelling. The importance of sampling has been first formulated in [4] as the problem of developing KD methods that are both query-efficient, and robust to labelling inaccuracies due to the imperfection of the teacher (i.e., *confirmation bias*). The method developed in [4] was designed for a pool-based setting, which represents an offline scenario where a pool of unlabeled data points is made available to the learner. We claim, in many real-world applications, a large number of unlabeled samples arrive in a streaming manner, **mak-**

ing it impossible to maintain all the data in a candidate pool. At the best of our knowledge, there exist not a framework supporting the development of AL methods that are both query-efficient, and robust to labelling inaccuracies in stream-based settings. This paper contribution are the following :

1. Formulate Stream-Based Active Distillation (SBAD) as the problem of developing AL methods that are both query-efficient, and robust to labelling inaccuracies, in stream-based settings.

2. Demonstrate the scheme applicability and benefits for large-scale video-based object detections on a public dataset [24].

3. Establish simple but effective baselines to train a YOLOv8n student from a YOLOv8x6 teacher. For that purpose, a GIT repository is provided.

2. Related Work

2.1. Knowledge Distillation

KD is a method that involves training a smaller model to imitate the performance of a larger model. The main objectives of this technique are to prevent a decrease in the model's performance when it operates on a dataset that is distributed differently than the source domain, referred to as Unsupervised Domain Adaptation (UDA), and to produce lightweight models suitable for the storage and computational capacities of miniaturized devices, referred to as Model Compression (MC) applications. In this study, we utilize a technique called *Self-training with knowledge distillation*, which was introduced by [26]. This technique trains a student model using pseudo-labels generated by a teacher model, which is beneficial when the labelled data is limited. However, it may also propagate errors or biases. Besides, we will discuss two additional techniques of interest in the following paragraphs: online distillation and context-aware distillation.

Online Distillation. This approach involves training a smaller student model to mimic the output of a larger teacher model on a per-example basis. In [11], the authors designed an online knowledge distillation scheme to perform real-time human segmentation in sports videos. Experiments show the model's ability to adapt to variations occurring in the context. Online distillation is also employed in [22] to adapt a low-cost semantic segmentation model to a target video where the data distribution is not necessarily stationary.

Context-aware Distillation. The researches [17, 26] attempt to exploit the contextual features of the scene to develop effective KD. They directly worked on the distillation scheme to develop more specialized students. For instance, in [17], they added a temporal dimension such that the student learns the variations in the teacher's intermediate features over time. They thus take into account frame redundancies within a CCTV stream.

2.2. Active Learning

AL is a sampling approach that selects the most informative data points to minimize the number of labels required for model training [31]. AL can be divided into three macro scenarios: membership query synthesis, pool-based AL, and stream-based AL [6]. The majority of approaches in deep AL have focused on the pool-based scenario, where the learner selects the most useful data points from a closed set of unlabeled observations. The stream-based AL scenario for object detectors has not been investigated. Moreover, AL assumes the availability of a perfect oracle, where the true label of a data point is revealed when queried. However, this assumption does not hold in a Knowledge Distillation (KD) framework, where the pseudo-labels provided by the teacher may be incorrect.

Active Learning for Image Classification. AL strategies for pool-based classification can be categorized into uncertainty-based or diversity-based approaches [34]. Uncertainty-based strategies estimate model uncertainty using techniques such as Monte Carlo dropout [16] or ensemble networks [21], while entropy and margin-based sampling strategies are also widely employed [27]. Task-agnostic methods like Learn loss [36] use a loss prediction module to estimate data points that are likely to be wrongly predicted. Among diversity-based strategies, Coreset [30] is one of the most popular, using a K-center Greedy algorithm to locate a set of representative data points. Cluster-Margin [12] combines uncertainty and diversity, while DRMRS [14] takes margin and diversity into account. BADGE [3] balances uncertainty and diversity using a $k-$MEANS++ seeding algorithm on gradients obtained from the last layer of the network. CDAL [1] replaces Euclidean distance with pairwise contextual diversity in the greedy

k-center algorithm used in Core-set. CLUE [23] performs uncertainty-weighted clustering to identify target instances that are both uncertain according to the model and diverse in feature space. VAAL [32] uses a Variational Autoencoder (VAE) to map instances into a latent space, which is then fed into a discriminator that learns to differentiate between labeled data and unlabeled samples.

Active Learning for Object Detection. AL approaches for object detection can be classified into black-box and white-box methods [28]. Black-box methods do not depend on the underlying network architecture and use informativeness scores such as the confidence obtained from the softmax layer, while white-box methods are dependent on the architecture of the underlying network. The minmax approach, which selects the least confident images among the unlabeled pool, is a popular black-box method [28]. Ensemble methods have also been used for object detection-oriented AL [15, 29]. Query strategies based on localization tightness and stability [19], mixture density networks [10], and a unified box regression and classification metric [37] has also been proposed. MIAL [38] is a multiple-instance framework that filters out noisy instances to bridge the gap between instance-level and image-level uncertainty. PPAL [35] is a two-stage algorithm that includes difficulty-calibrated uncertainty sampling and category-conditioned matching similarity. [18] proposed to cluster the unlabeled observations in groups based on the frequency domain values and to use different sampling rates for each group.

2.3. Challenges of Stream-based Active Distillation

The importance of sampling has been first formulated in [4] as the problem of developing KD methods that are both query-efficient and robust to labeling inaccuracies due to the imperfection of the teacher (i.e., *confirmation bias*). Their methods provide a theoretical guarantee that the scheme leads to queries where the teacher provides correct labels. However, this approach has been developed in a pool-based setting where the student has access to the entire information pool. Therefore, techniques such as diversity-based strategies, clustering, or pairwise distance matrices may not be feasible, especially in contexts with spatio-temporal correlation among the data that could be exploited. Another aspect is that, due to the complexity of the student model, uncertainty techniques relying on Monte Carlo dropout or Learn loss modules may not be viable options.

3. Problem Statement

Let $\theta^{base}_{student}$ define a compact general pre-trained model learning the distribution $\mathcal{D}$ of a data stream $\mathcal{X}$. We assume a spatio-temporal correlation among the data. The student is endowed with SELECT (I_t), a rule that decides whether to query the image for pseudo-labelling by a powerful but imperfect model $\theta^{general}_{teacher}$. The objective is to train a high-performing student by querying the minimum number of teacher soft-labels. We assume a large-scale setting (e.g., city-scale deployment of CCTV, monitoring of large construction sites) and affordable hardware. Therefore, the pseudo-labels constituting a training set $\mathcal{L}$ must not exceed a maximal budget per student B, i.e., $|\mathcal{L}| \leq B$. It is important that the SELECT strategies used in SBAD are computationally efficient for two reasons. Firstly, to prevent adding unnecessary complexity to the student models. Secondly, to allow for quick sampling decisions. If the decision time for a selection rule is higher than the frame rate used by the CCTV system, it would require the system to have a buffer for temporarily storing recently seen images until the sampling decision is made. This would inevitably result in the system requiring additional resources to store and process the data, which is not feasible in large-scale settings where hardware resources are limited.

Algorithm 1 SBAD Framework

Require: a pre-trained student model $\theta^{base}_{student}$, a general purpose teacher model $\theta^{general}_{teacher}$, a budget B, a SELECT strategy.
Ensure: $B \geq 1$
  $\mathcal{L} \leftarrow \emptyset$ ▷ Selected frames
  $t \leftarrow 0$ ▷ Timestamp
  while $|\mathcal{L}| \leq B$ **do**
    Observe current frame I_t
    if SELECT(I_t) **is** TRUE **then**
      $\{b_i\} \leftarrow \theta_{teacher}(I_i)$ ▷ Pseudo-labels
      $\mathcal{L} \leftarrow \mathcal{L} \cup (I_t, \{b_i\}_t)$
    end if
    $t \leftarrow t + 1$
  end while
  return update$(\theta^{base}_{student}, \mathcal{L})$

Figure 1. provides a visual illustration of the SBAD framework. The sampling phase is a critical step in which frames are selected based on instance

selection criteria to obtain the most informative samples. The selected frames are then queried by the teacher model to generate pseudo-labels that are subsequently used for fine-tuning the student models. In the model development phase, the fine-tuned models can be evaluated using hard-labels, but in real-world deployment scenarios, there are typically few or no labels available, making this step impractical.

4. Methodology

In the context of stream-based active learning, the single-pass evaluation of data points is often addressed by applying a threshold to certain informativeness scores [7–9, 13, 25]. However, this approach has not been tested in online active distillation tasks for object detection. In this paper, we investigate the effectiveness of thresholding algorithms based on the confidence of the base student model $\theta^{base}student$ for the SBAD framework. At round t, when the student model $\theta^{base}student$ observes an image I_t, $n \geq 0$ objects are detected, which are defined by the bounding boxes b_{it} and confidence scores c_{it}. According to [28], a unique confidence score C_t for I_t can be obtained using:

$$C(I_t) \coloneqq \max_i c_{it}$$

This means that the confidence of each image is approximated by the highest confidence score among the objects detected in that image. By using this confidence metric, we can then apply a threshold Δ to the confidence scores of the incoming frames. The overall structure of the top confidence threshold sampling scheme is presented in Algorithm 1. To estimate the threshold Δ for selecting the most informative frames, we introduce a warm-up phase where the student model $\theta^{base}student$ observes incoming frames for a period of length w without querying any image and without storing anything other than a single scalar representing the image-level confidence scores $C(I_t)$, where $t = 1, ..., w$. At the end of the warm-up phase, the student model estimates an $(1 - \alpha)$-upper percentile on the distribution of the confidence scores, where α represents the desired sampling rate. In other words, we aim to select the frames to pseudo-label and fine-tune $\theta^{base}student$ with a ratio of α frames out of the total number of frames. While in traditional AL, the focus is on querying images that the student model is least confident about, this approach may not be optimal for stream-based KD scenarios. The least confident images often correspond to very hard examples that may not be informative enough for the student model in the early rounds of AL when it has not been fine-tuned for the specific scene. Additionally, selecting images with high uncertainty for pseudo-labeling may lead to confirmation bias as the pseudo-labels may not align with the ground truth due to the imperfection of the teacher model $\theta^{general}_{teacher}$ as an oracle. To address these issues, we propose to let the student model $\theta^{base}_{student}$ query the most confident frames based on a threshold Δ given by:

$$\mathbb{P}(C(I_t) \geq \Delta) = \alpha$$

"Distillation"Ideally, using this threshold, the student will sample informative examples that the teacher model would properly pseudo-label and that will contribute to faster fine-tuning while avoiding frames that are too uncertain to be used in the initial stages of AL.

5. Experiments

5.1. Experimental Settings

Dataset In order to evaluate the effectiveness of the SBAD approach, we utilized the WALT dataset [24], which consists of multi-camera recordings. The dataset provides spatial and temporal diversity, including various points of view and lighting conditions (day and night).

Distillation implementation In line with the principles of data distillation proposed by Rivas et al. [26], we employ a large and complex teacher model, YOLOv8x6 (261.1 GFLOPs), to generate pseudo-labels. These labels are then utilized to train several smaller student models, YOLOv8n (8.7 GFLOPs), with less architectural complexity. Both networks are initially pre-trained on the COCO dataset [20]. The student models are re-trained for 100 epochs with a batch size of 16. The budget of the SBAD framework is determined by the number of pseudo-labels used for fine-tuning, which ranges from 25 to 250 in our experiments.

Methods. As the SBAD problem for object detection has not been explored before, there are not many state-of-the-art methods that can be used. To explore the effectiveness of the confidence-based thresholding algorithm, we used different baselines. First, a naïve *N-First* approach has been implemented, where the student models are fine-tuned by simply

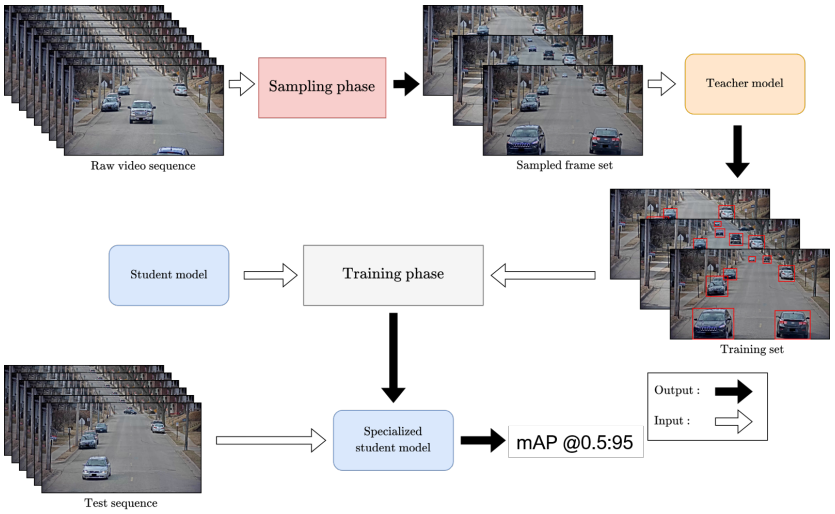

Figure 1. SBAD pipeline: sampling, fine-tuning, and evaluation.

taking the first N images observed from each camera. A second baseline is given by a *random* sampling approach, where a number $s \sim U(0,1)$ is generated for each incoming frame, which is queried only if $s \geq 1 - \alpha$. A third baseline is given by a more active learning-oriented *least confidence* approach, where similarly to the top confidence case, we impose a threshold on the image-level confidence score. The main difference is that the threshold Δ is estimated by taking the α-lower percentile from the warm-up set $\mathcal{W}$.

5.2. Experimental Results

Figures 2. and 3. shows the learning curves obtained using stream-based active learning techniques on the WALT dataset. Our analysis can be approached from two perspectives. Firstly, from a knowledge distillation standpoint, we observed how the student model's performance improves as we use more frames for fine-tuning. In particular, we found that the mAP50-95 score approaches that of the teacher model when 250 pseudo-labeled frames are used. However, we also noticed that the student's performance deteriorates significantly when only a small number of frames are used for fine-tuning, which could be attributed to overfitting due to the limited number of images presented to the network. In addition, if the model is fine-tuned on images biased towards a specific time of day, such as only night or day, it may perform poorly on the balanced test set used for evaluation. Furthermore, as depicted in Figure 4., choosing highly uncertain images for pseudo-labeling may lead to incorrect labels due to the teacher's own bad prediction.

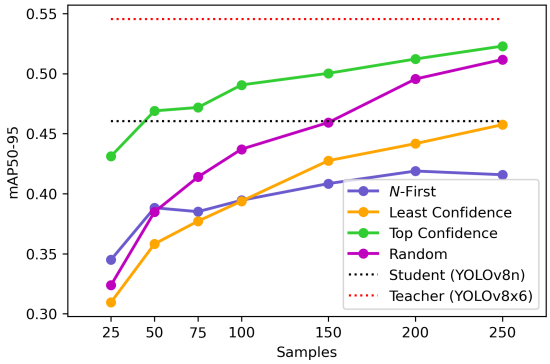

Figure 2. Learning curves obtained on the first two cameras of WALT. Results show that increasing the number of frames used for fine-tuning improves the student model's performance, approaching that of the teacher model with 250 frames. However, using only a small number of frames may lead to overfitting and poor performance on balanced evaluation sets. Top confidence thresholding is more effective than least confidence-based methods for stream-based active learning, highlighting the importance of avoiding highly uncertain images during fine-tuning.

From an active learning perspective, the performance achieved with the *top confidence threshold* algorithm is significantly better than that obtained using the least confidence-based method. This highlights the importance of fine-tuning the model with highly certain images, especially when the model has not yet been specialized for the scene.

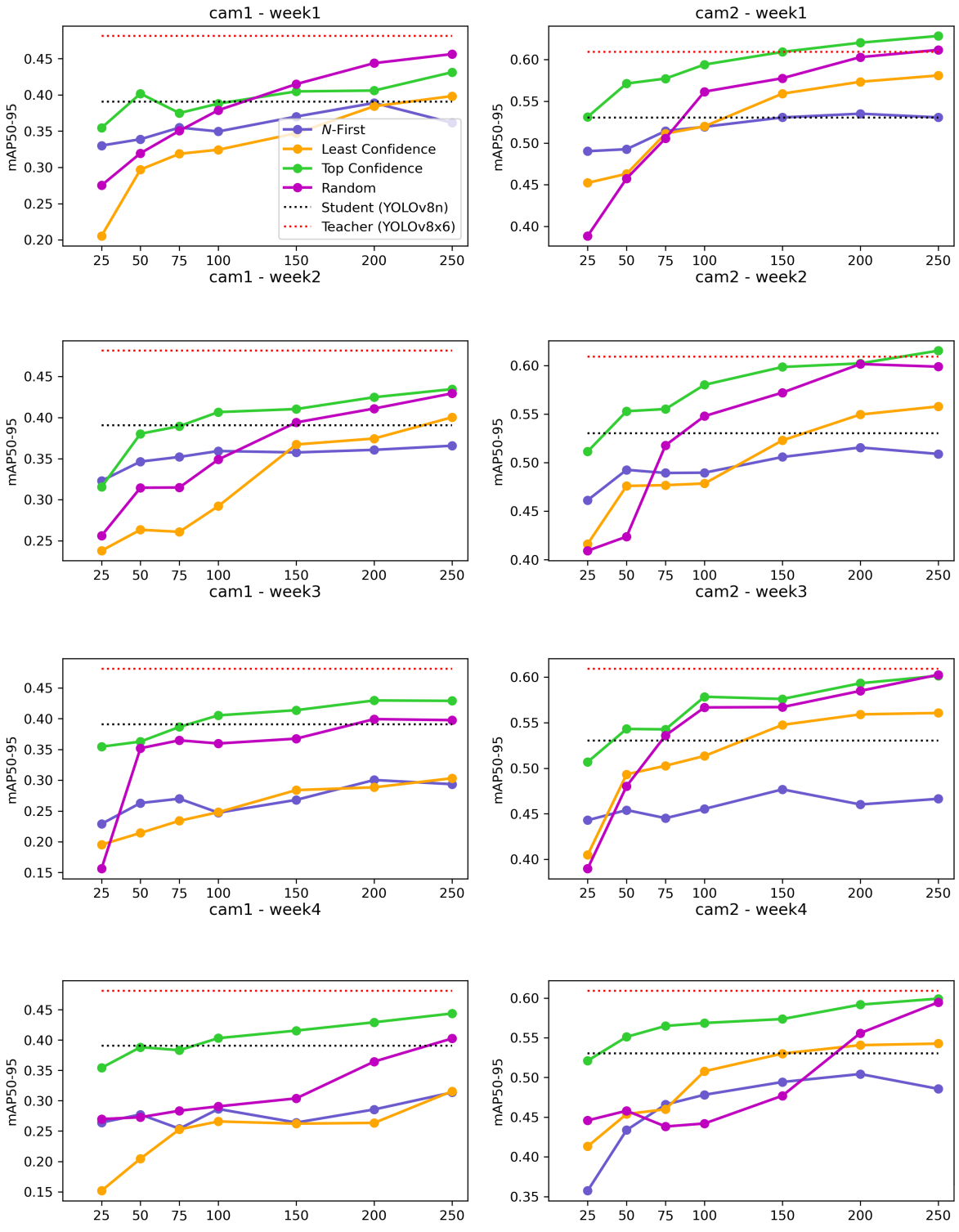

Figure 3. Weekly analysis on the first two cameras of WALT.

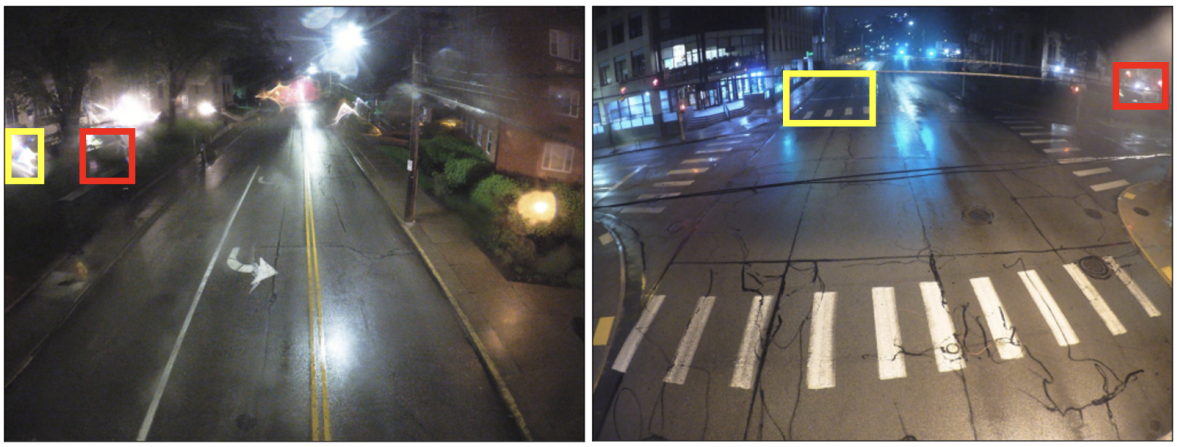

Figure 4. Two difficult examples (one for each camera) that lead to *confirmation bias*: when the student requests highly uncertain images based on its predictions (in yellow), wrong pseudo labels are revealed (in red).

6. Conclusion

This paper proposes SBAD to bridge the gap between large-scale and affordable deep learning models while adapting to changing environments. This framework enables the scalable deployment of deep learning models under tight budget constraints.

The framework evaluates the informativeness of each frame, accounting for teacher imperfections in a KD scheme. Experiments demonstrate that traditional AL strategies may not be optimal for KD. Future research could explore alternative sampling strategies and distillation mechanisms to improve performance.

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