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# A semi-supervised Teacher-Student framework for surgical tool detection and localization

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## ABSTRACT

Surgical tool detection in minimally invasive surgery is an essential part of computer-assisted interventions. Current approaches are mostly based on supervised methods requiring large annotated datasets. However, labelled datasets are often scarce. Semi-supervised learning (SSL) has recently emerged as a viable alternative showing promise in producing models retaining competitive performance to supervised methods. Therefore, this paper introduces an SSL framework in the surgical tool detection paradigm, which aims to mitigate training data scarcity and data imbalance problems through a knowledge distillation approach. In the proposed work, we train a model with labelled data which initialises the Teacher-Student joint learning, where the Student is trained on Teacher-generated pseudo-labels from unlabelled data. We also propose a multi-class distance with a margin-based classification loss function in the region-of-interest head of the detector to segregate the foreground-background region effectively. Our results on m2cai16-tool-locations dataset indicates the superiority of our approach on different supervised data settings (1%, 2%, 5% and 10% of annotated data) where our model achieves overall improvements of 8%, 12%, and 27% in mean average precision on 1% labelled data over the state-of-the-art SSL methods and the supervised baseline, respectively. The code is available at <https://github.com/Mansoor-at/Semi-supervised-surgical-tool-detection>.

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## KEYWORDS

Semi-supervised learning;  
Faster-RCNN; surgical tool  
detection

## 1. Introduction

Recent works in deep learning (DL) based on visual recognition methods have delivered enormous advantages towards computer-assisted interventions (CAIs) (Ward et al. 2021). CAI tools have been primarily focused on specific information gathering, such as the presence or location of lesions. Nonetheless, recent developments in the image recognition tasks with improved accuracy have led to expansion of its scope to several other areas including intraoperative decision support systems (Bouget et al. 2017). These applications provide contextual information to the surgeon during the surgery, as a postoperative feedback (Bhatia et al. 2007; Sarikaya et al. 2017) for surgical training and video content analysis (Wang et al. 2019).

More recently, CAI systems capable of performing effectively the sub-tasks such as surgical phase recognition, identification of the tool presence and their recognition, localisation and instance-based segmentation are getting increased attention (Bouget et al. 2017). The development of these task-based automated approaches can ensure improved surgical care and patient safety and alleviate surgeon fatigue.

DL-based surgical tool detection task has attracted a lot of attention in recent years. However, most of the state-of-the-art (SOTA) methods have employed fully supervised approaches (Jin et al. 2018; Zhang et al. 2020), and only a few weakly supervised methods, mostly implementing classification models for determining tool presence (Vardazaryan et al. 2018), have been proposed. Nonetheless, training complex DL models under the supervised setting requires difficult-to-acquire and

precisely annotated datasets, which is a time-consuming task and susceptible to intra- and inter-observer bias in annotations. As a result, only a few labelled surgical tool datasets are publicly available (Sarikaya et al. 2017; Jin et al. 2018), and this lack of annotated datasets has essentially hindered the development of robust and generalisable deep architectures for the surgical instrument detection.

Alternatively, the annotation cost could be greatly mitigated by exploiting unlabelled data through efficient semi-supervised learning (SSL) frameworks. The core idea of SSL is to be able to extract information from the unlabelled data that is essential for label prediction. One solution is to train a network to solve a pre-defined pretext task (Teacher model generating pseudo labels) and then using the learned knowledge in the downstream task (Student network). Recently, SSL has shown promising outcomes in improving model performance and is receiving growing attention of the computer vision research community (Van Engelen and Hoos 2020; Sohn et al. 2020). Despite these progresses, most of these advances are in the domain of image classification rather than object detection as the bounding box annotations require more time and effort to generate. Traditionally, SSL can be approached with adapting state-of-the-art (SOTA) image classification methods such as method proposed by Sohn et al. (2020) for object detection. However, the existence of some unique characteristics such as foreground-background and foreground class imbalance make object detection interact poorly with those methods. The class imbalance problem may greatly impede the use of pseudo-labelling-based training pipelines since Teacher-generated

pseudo labels will be overly biased towards dominant classes and ignoring minor and less dominant classes. As a result, adapting image classification to object detection will likely exacerbate the class-imbalance problem and cause severe overfitting.

To overcome these issues, we propose a jointly trained Teacher–Student model on m2cai16-tool-locations dataset (Jin et al. 2018) which is initialised by a supervised detector. We argue that slowly updating the Teacher by exponential moving average (EMA) via the Student can alleviate pseudo-labelling bias problem and improve pseudo label quality and, hence, overall performance improvement. Additionally, we propose a multi-class distance and margin-based classification loss in the region-of-interest (ROI) head of the detector network to boost the classification performance. This is achieved by maximising the distance between foreground classes and the background. To the best of our knowledge, our approach is the first effort towards leveraging Teacher–Student joint training paradigm for addressing data scarcity problem in surgical tool detection applications. We employ strong and weak augmentation pipelines to improve model robustness (Figure 1(b)). Our proposed pipeline outperforms supervised baseline and other SOTA semi-supervised methods in terms of classification and localisation performance (Figure 1(a)).

In the rest of the paper, we discuss related work (Section 2), materials and method (Section 3), quantitative and qualitative results (Section 5), ablation studies (Section 5.3) and lastly discussion and conclusion (Section 6).

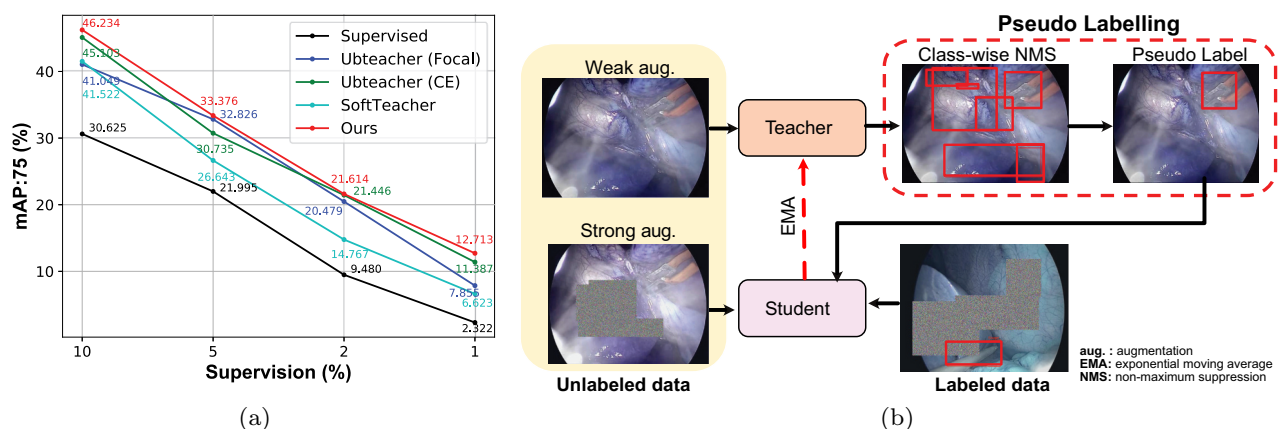
## 2. Related work

Some of the early works on surgical tool detection used radio-frequency identification tags (Kranzfelder et al. 2013), Viola–Jones detection algorithm (Lalys et al. 2011) and segmentation, contour delineation and three-dimensional modelling (Speidel et al. 2009). With the advent of DL-based approaches using convolutional neural networks, computer vision methods have evolved with remarkable growth and demonstrated promising outcomes (Russakovsky et al. 2015). In the surgical domain, several works have leveraged DL approaches to obtain SOTA

performance on surgical instrument detection (Sahu et al. 2016; Twinanda et al. 2016a; bJin et al. 2018).

Most of the studies conducted on surgical tool detection have proposed supervised pipelines or only have targeted frame-level tool presence detection. For example, AGNet (Hu et al. 2017) used global and local prediction networks to obtain visual cues for tool presence detection and showed a significant improvement over m2cai16-tool challenge (Raju et al. 2016) winners. Jin et al. (2018) proposed region-based convolutional neural network to perform surgical skill assessment adapted to tool presence detection, spatial localisation and tracking. The authors also extended the m2cai16-tool dataset<sup>1</sup> to include tool bounding boxes (subsequently named as m2cai16-tool-locations) which we have used in this work. Sarikaya et al. (2017) used image and temporal motion cues to train multi-modal convolutional neural network (CNN) models for tool detection and localisation in robotic-assisted surgical training task videos. Tool detection and pose estimation were also studied by Reiter et al. (2012), but it was limited to robotic arms that return kinematic data. Shi *et al.* proposed a lightweight attention-guided framework (Shi et al. 2020a) for tool detection and conducted an ablation study on three different datasets (two public datasets, EndoVis Challenge (Kurmman et al. 2017) and ATLAS Dione (Sarikaya et al. 2017) and one self-prepared cholec80-locations). However, their model performed well on all tools except grasper and irrigator classes. In another study (Zhang et al. 2020), irrigator can be observed as worst performing instrument with average precision (AP) of 41.6%, followed by grasper with 54.1% in a supervised setting at intersection-over-union (IoU) threshold of 50%. A ghost feature map-based pipeline was used to reduce the computational burden for tool detection in Yang et al. (2021). A CNN-based hidden Markov model was proposed by Twinanda et al. (2016a) for surgical tool detection from laparoscopic videos. A combination of CNN to extract spatial features and long–short-term memory for temporal cues was proposed to perform surgical tool detection from laparoscopic videos (Mishra et al. 2017).

Although the results of some of these approaches have been mostly encouraging, they have reported only one mean



**Figure 1.** Comparison at different percentages of supervision and augmentation strategies in a Teacher–Student paradigm. (a) The proposed approach efficiently leverages unlabelled data and produces substantial improvement over supervised baseline and on the state-of-the-art Unbiased Teacher (Ubteacher) Liu et al. (2021) framework. (b) Data augmentation workflow of the proposed Teacher–Student mutual learning approach. Unlabelled data given with weak augmentation to Teacher and with strong augmentation to Student. Student gets pseudo labels through non-maximum suppression and thresholding from the Teacher.

average precision (mAP) result (Sarıkaya et al. 2017; Shi et al. 2020b) which is not quite sufficient to gauge the classification and localisation performance. Furthermore, previous approaches require completely labelled datasets to train the model. Such datasets are either scarcely available or the process of annotating them can lead to other issues such as introducing unintended biases in the trained model.

In this work, we aim to demonstrate the advantages of an SSL approach and propose a novel semi-supervised Teacher–Student framework to alleviate the limited data problem and annotation cost requirement for training on larger datasets. Our literature search revealed that there are only two studies conducted on SSL in the medical domain where one is based on cataract surgery dataset (Jiang et al. 2021) while another study (Yoon et al. 2020) used a tracker to detect instruments from unlabelled private surgery videos. To the best of our knowledge, this is the first approach that investigates the effectiveness of unlabelled data through a Teacher–Student learning pipeline for tool detection on a minimally invasive surgery dataset. We report results from our model in terms of mAP on various IoU thresholds to demonstrate the effectiveness of our approach in detecting and localising surgical tools.

### 3. Materials and method

#### 3.1. Dataset

In this work, we use an extended version of the m2cai16-tool dataset which was originally released for M2CAI 2016 Tool Presence Detection Challenge (Twinanda et al. 2016b). This dataset consists of 15 videos each with duration from 20 to 75 min of cholecystectomy procedures performed at the University Hospital of Strasbourg in France. After down sampling at 1 fps, it leaves 23,000 frames annotated with tool presence classification.

Later, m2cai16-tool-locations dataset was built with spatial bounding box annotations (Jin et al. 2018). This dataset consists of a total of 2812 frames that were annotated under supervision and spot-checking from clinical experts. We have used 80%, 10% and 10% for training, validation and test splits, respectively. The annotations breakdown per class is given in the Supplementary material (Table S1), and the tool instances with example box annotations are presented in Figure 2.

We use AP computed per class and mAP for all seven classes which are the standard object detection evaluation metric. These metrics are evaluated at different IoU thresholds, usually denoted as  $mAP_{IoU-threshold}$ . We report results for 50%, 75%, 50:95% (average of AP values for IoU thresholds from 50% to 95% with interval of 5%), medium and large IoU thresholds.

#### 3.2. Data augmentation

We have used two data augmentation strategies in this work, which we refer as weak and strong augmentations (Figure 1(b)). For the weak augmentation, we apply random horizontal flips, whilst for strong augmentation, we randomly perform several photometric augmentations like greyscale, colour jittering, Gaussian blur, patch masking and cut-out patches DeVries and Taylor (2017). For the complete description of data augmentation with parameter values, please refer to Liu et al. (2021).

### 4. Method

In this work, we address multi-instance surgical tool detection problem in a semi-supervised setting. Let the training set in various arrangements of labelled datasets be denoted as  $D_s = \{x_i^s, y_i^s\}_{i=1}^{N_s}$  and unlabelled datasets be  $D_u = \{x_i^u\}_{i=1}^{N_u}$ , where  $N_s$  and  $N_u$  represent number of supervised and unsupervised training samples, while  $y^s$  represents bounding box annotation of each labelled image  $x^s$ . Here,  $y^s$  consists of bounding boxes for all object instances, height and width of image and instance category names. It is important to mention that since all the training data samples contain labels, during training, we removed the labels of the portion we categorise as unlabelled. The overall training pipeline is divided into two stages as shown in Figure 3. The first stage is the initialisation stage (Section 4.1), while the second is the Teacher–Student joint learning mechanism (Section 4.2). In the second stage, the Teacher generates pseudo-labels, and Student network is trained on both pseudo labelled data and supervised data. Each stage is detailed separately below along with Student learning and Teacher update scheme and margin.

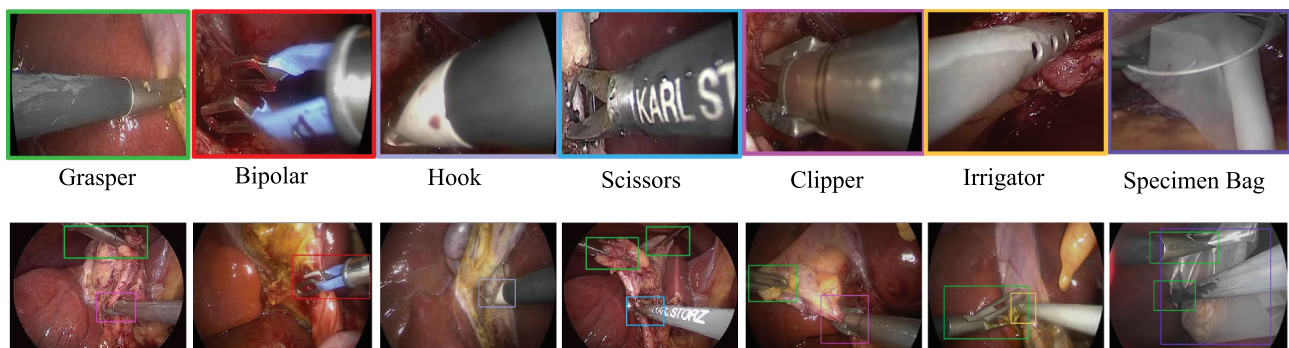
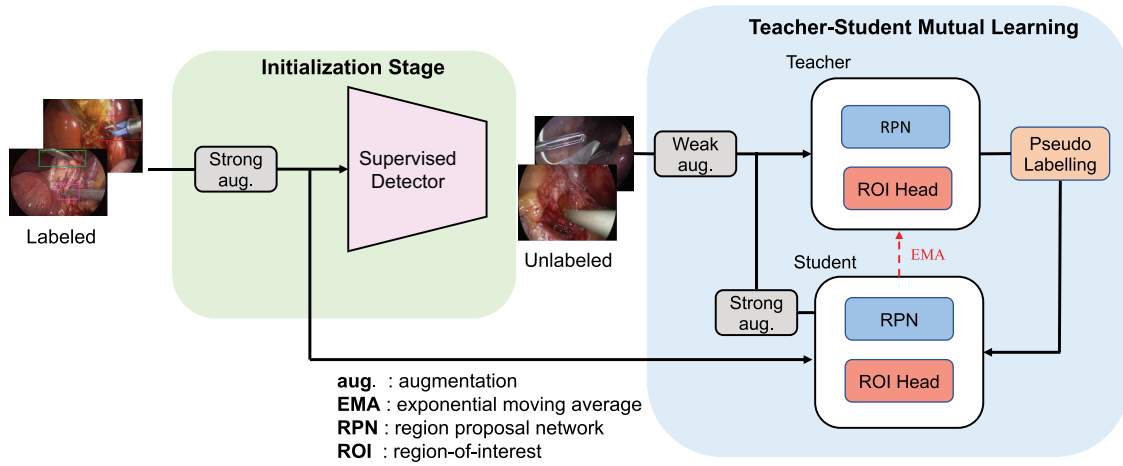


Figure 2. (Top) Samples from *m2cai16-tool-locations* dataset with representative classes of seven tools. (Bottom) Example frames with bounding box annotations where colour of the box refers to tool class.





**Figure 3.** Overview of the proposed Surgical tool detection model. It consists of two modules: (1) an initialisation module, where a supervised model makes use of strongly augmented labelled data, and (2) a Teacher–Student mutual learning module, where the Student is trained with strongly augmented unlabelled data with Teacher-generated pseudo labels. The Student transfers learned weights to the Teacher gradually through exponential moving average (EMA).

#### 4.1. Initialisation stage

The initialisation stage acts as a trigger point for Teacher–Student joint learning. It sets the stage for the Teacher model to be able to generate qualitative pseudo-labels for better Student learning. In this stage, we exploit the available labelled data  $D_s = \{x_i^s, y_i^s\}_{i=1}^{N_s}$  to train the Faster-RCNN detector model ( $\theta$ ) with supervised loss  $\mathcal{L}_{sup}$ . The standard Faster-RCNN model makes use of four losses: RPN classification loss  $\mathcal{L}_{cls}^{rpn}$ , RPN regression loss  $\mathcal{L}_{reg}^{rpn}$ , ROI classification loss  $\mathcal{L}_{cls}^{roi}$  and ROI regression loss  $\mathcal{L}_{reg}^{roi}$  (Equation (1)).

$$\mathcal{L}_{sup} = \sum_i^{N_s} \mathcal{L}_{cls}^{rpn}(x_i^s, y_i^s) + \mathcal{L}_{reg}^{rpn}(x_i^s, y_i^s) + \mathcal{L}_{cls}^{roi}(x_i^s, y_i^s) + \mathcal{L}_{reg}^{roi}(x_i^s, y_i^s) \quad (1)$$

The weights and architecture of the model trained during this initialisation phase are then copied to be used for both the Student and Teacher models ( $\theta_T \leftarrow \theta, \theta_S \leftarrow \theta$ ). The trained detector from this stage provides a good initialisation for next stage, where we further exploit unsupervised data to improve object detection.

#### 4.2. Teacher–Student joint learning stage

The proposed knowledge distillation framework leverages Student and Teacher joint training to address lack of data problem. During training, Teacher generates pseudo labels on unlabelled data and Student is trained on those labels. Thus, a continuously learning Student passes on the learned knowledge to the Teacher. We posit that this evolving mutual learning would result in better detection performance by generating stable and reliable pseudo labels. Weak and strong augmentation pipelines ensure reliable pseudo label generation by Teacher and diversity in Student models, respectively.

#### 4.3. Student learning and Teacher update scheme

We tackle the pseudo-label noise problem which may cause severe performance degradation (Sohn et al. 2020) by

confidence thresholding ( $\tau$ ). Although this step could have sufficed in the case of image classification, for object detection tasks, additional steps must be enforced as duplicated bounding box predictions, and class-imbalanced prediction problems are typically encountered in these settings. We address the duplicated box predictions problem by applying class-wise non-maximum suppression (NMS) before a confidence thresholding step. As simple confidence thresholding only removes samples with low confidence on predicted object categories and does not take into account the quality of bounding box locations, we do not use unsupervised loss on bounding box regression which is thus represented as below with  $\theta_S$  as weight updates between both supervised  $\mathcal{L}_{sup}$  and unsupervised  $\mathcal{L}_{unsup}$  losses:

$$\mathcal{L}_{unsup} = \sum_i^{N_u} \mathcal{L}_{cls}^{rpn}(x_i^u, \tilde{y}_i^u) + \mathcal{L}_{cls}^{roi}(x_i^u, \tilde{y}_i^u) \quad (2)$$

$$\theta_S \leftarrow \theta_S + \gamma \frac{\partial(\mathcal{L}_{sup} + \lambda_u \mathcal{L}_{unsup})}{\partial \theta_S}, \quad (3)$$

where  $\gamma$  is the learning rate and  $\lambda_u$  is the unsupervised loss weight. The overall unsupervised loss in Equation (2) consists of the sum of RPN and ROI head classification losses. Equation (3) depicts the Student weight update scheme which includes both supervised and unsupervised losses with a loss weight parameter  $\lambda_u$ .

Finally, we perform Teacher model refinement by using EMA following *Mean Teacher* to slowly update Teacher network which in turn will generate stable and reliable pseudo labels. The update can be represented as:

$$\theta_T \leftarrow \alpha \theta_T + (1 - \alpha) \theta_S, \quad (4)$$

where  $\alpha$  is the EMA rate, and  $\theta_T, \theta_S$  are the network weights for Teacher and Student.

#### 4.4. Logistic loss with added margin and distance penalisation

In the surgical domain, foreground class imbalance exists in every dataset due to the fact that tool usage frequency varies from one tool to another (Mishra et al. 2017). In this work, to

address the class imbalance problem, we target the foreground and background class imbalance problems by introducing a multi-class loss function based on a margin, which tries to maximise foreground–background distance. Unlike the focal or cross entropy losses, our proposed loss tries to predict relative distance between inputs. Specifically, we divide classification logits between foreground and background instances and then compute *sigmoid* probability, respectively. We then sum the *softmax* of the probabilities over all the batch for the foreground  $\rho$  and background  $\beta$  instances. These probabilities are then used to maximise foreground–background distance in the final loss computation which is in the form of a logistic loss function for classification defined as

$$\mathcal{L}_{cls}^{roi} = \sum_n w_l \log\left(1 + \frac{e^{s \cdot (\beta - \rho + \sigma)}}{s}\right), \quad (5)$$

where  $n$  is the mini-batch size,  $w_l$  represents loss weight,  $s$  is the smoothness parameter and  $\sigma$  denotes margin.

Apart from the multi-class loss, Teacher update with EMA will also help reduce pseudo label bias since new Teacher is regularised by previous Teacher model which prevents drastic movement of the decision boundary towards under-represented classes.

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**Algorithm 1** Multi-class distance and margin-based classification loss

---

```

1: procedure losslogits, targets
2:   classes  $\leftarrow$  class_indices
3:   g_logits  $\leftarrow$  logits(targets = classes)
4:   bg_logits  $\leftarrow$  logits(targets! = classes)
5:   fg_prob  $\leftarrow$  sigmoid(fg_logits)
6:   bg_prob  $\leftarrow$  sigmoid(bg_logits)
7:    $\rho \leftarrow \sum$  softmax(fg_prob)
8:    $\beta \leftarrow \sum$  softmax(bg_prob)
9:   loss  $\leftarrow$  Eq : 5
10: end procedure

```

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## 5. Experiments and results

### 5.1. Implementation details

The implementation of our proposed framework is based on Faster-RCNN detector model with ResNet50-FPN backbone, whose network weights are initialised by ImageNet pretrained model. We use a confidence threshold ( $\tau$ ) of 0.7, regularisation co-efficient for unsupervised loss ( $\lambda_u$ ) of 0.2 and EMA rate ( $\alpha$ ) of 0.9996. We use *WarmupMultiStepLR* as a learning rate ( $\alpha$ ) scheduler in initialisation stage while a constant learning rate of 0.01

for the Teacher–Student mutual learning stage. In the initialisation stage, we use strong augmentation, while during the Teacher–Student mutual learning, we use weak augmentation for the Teacher and strong augmentation for Student. We report results in terms of mAP on different IoU thresholds. We use a batch size of 8 (4 labelled images and 4 unlabelled images) throughout the experiments. We performed network training through detectron2 (Wu et al. 2019) object detection framework using 4 graphical processing units (GPUs) on NVIDIA Tesla P100-SXM2-16GB system. We use fixed seed values for generating the data splits to make the results more reproducible.

## 5.2. Results

### 5.2.1. Quantitative results

We evaluate our model with different labelled and unlabelled data protocols and present the results on a 10% held-out set in Table 1. The table also includes results on the supervised baseline, UnbiasedTeacher (Liu et al. 2021), with both CrossEntropy and focal losses and SoftTeacher (Xu et al. 2021). Table 2 shows per class  $mAP_{50:95}$  results on 1% labelled data setting. Furthermore, we also conduct a paired  $t$ -test between  $AP_{50}$  obtained by our proposed model and  $AP_{50}$  obtained by other SOTA methods. The resulting box-plot on 1%, 2%, 5% and 10% labelled data setting is shown in Figure 5, and  $p$ -values are shown in Table 1.

### 5.2.2. Qualitative results

In this section, we report the qualitative performance of our model as shown in Figure 4. The example of surgical scenes is carefully chosen to contain several instances in one frame (column 2 from left), only partially visible instrument (column 3 from left) and irregular orientation (column 4 from left). Results on all data settings have been presented to see how well model performs in terms of detection and localisation.

## 5.3. Ablation study

Several ablation studies were conducted to validate the effectiveness of different parameters. We evaluated the effect of initialisation, confidence threshold ( $\tau$ ), EMA rates and normalisation parameter ( $s$ ) on model performance. We trained the model with and without initialisation stage and concluded that such process does improve the overall performance by a substantial margin (Supplementary material section 1.1). We also evaluated the model on different values of  $\tau$  where  $\tau = 0.7$  gives the best performance (Supplementary material section 1.2). We also performed multiple experiments to evaluate the impact of Teacher update with EMA rate on model performance for which EMA of 0.9996 gave the optimum performance (Supplementary material section 1.3).

Here, we present ablation for use of different loss functions and our proposed loss with different normalisation parameter ' $s$ ' values. It can be observed that our proposed loss with  $s = 5$  provided the best performance with the highest mAP over all IoU thresholds (see Table 3).

**Table 1.** Experimental results with ResNet50-FPN as backbone.

Method	1% Labelled data					<i>p</i> -Values
	$mAP_{50}$	$mAP_{50:95}$	$mAP_{75}$	$mAP_m$	$mAP_l$	
Supervised	23.578	7.673	2.322	6.189	9.050	5.996e-17
Unbiased Teacher* (Liu et al. 2021)	34.374	14.145	7.855	10.687	15.880	5.626e-02
Unbiased Teacher** (Liu et al. 2021)	42.382	18.008	11.387	13.041	20.135	6.229e-03
SoftTeacher (Xu et al. 2021)	38.421	13.556	6.623	16.756	13.045	5.526e-02
Ours	50.632	20.094	12.713	15.219	21.774	–
<b>2% Labelled data</b>						
Supervised	47.140	18.609	9.480	24.033	18.586	2.558e-14
Unbiased Teacher* (Liu et al. 2021)	71.608	31.752	20.479	27.871	32.430	3.975e-04
Unbiased Teacher** (Liu et al. 2021)	72.416	31.490	21.446	26.767	32.666	2.010e-01
SoftTeacher (Xu et al. 2021)	60.366	25.421	14.767	17.991	28.323	2.558e-8
Ours	72.341	32.311	21.614	29.780	33.556	–
<b>5% Labelled data</b>						
Supervised	71.082	32.249	21.995	29.505	35.041	5.866e-05
Unbiased Teacher* (Liu et al. 2021)	84.721	42.269	32.826	35.697	44.204	1.298e-01
Unbiased Teacher** (Liu et al. 2021)	82.592	40.393	30.735	33.665	42.904	3.424e-04
SoftTeacher (Xu et al. 2021)	83.211	38.857	26.643	30.567	40.718	4.566e-04
Ours	84.427	42.392	33.376	31.156	44.610	–
<b>10% Labelled data</b>						
Supervised	80.193	38.640	30.625	29.845	40.958	7.108e-03
Unbiased Teacher* (Liu et al. 2021)	92.981	47.369	41.049	41.137	48.714	2.291e-01
Unbiased Teacher** (Liu et al. 2021)	90.353	45.972	45.103	39.247	47.787	1.00
SoftTeacher (Xu et al. 2021)	89.362	42.717	41.522	38.312	43.849	1.00
Ours	90.250	46.886	46.234	42.635	48.644	–

\* With Focal Loss; \*\* with Cross Entropy Loss.

**Table 2.** The average precision ( $AP_{50:95}$ ) per class on 1% labelled data.

Class	Supervised	Ubteacher*	Ubteacher**	SoftTeacher	Ours
Grasper	12.434	23.457	23.046	7.0	20.203
Bipolar	13.450	19.472	33.384	22.2	29.499
Hook	11.349	38.529	44.614	29.8	43.924
Scissors	3.592	4.130	5.052	3.8	6.860
Clipper	4.273	5.045	4.800	0.0	4.970
Irrigator	4.022	3.393	8.468	27.9	10.331
SpecimenBag	4.592	4.986	6.692	4.1	24.873

\* Unbiased Teacher with focal loss; \*\* Unbiased Teacher with cross entropy loss.

**Table 3.** Normalisation parameter  $s$  grid search.

Loss	$mAP_{50:95}$	$mAP_{50}$	$mAP_{75}$	$mAP_m$	$mAP_l$
Focal	14.145	34.374	7.855	10.687	15.880
Cross entropy	18.008	42.382	11.387	13.041	20.135
Proposed loss ( $s = 3$ )	16.260	41.438	8.260	10.801	18.848
Proposed loss ( $s = 4$ )	18.475	44.534	9.252	13.246	20.483
Proposed loss ( $s = 5$ )	<b>20.094</b>	<b>50.632</b>	<b>12.713</b>	<b>15.216</b>	<b>21.774</b>
Proposed loss ( $s = 6$ )	18.993	47.597	11.156	10.380	22.006

Note: Best values are provided in bold.

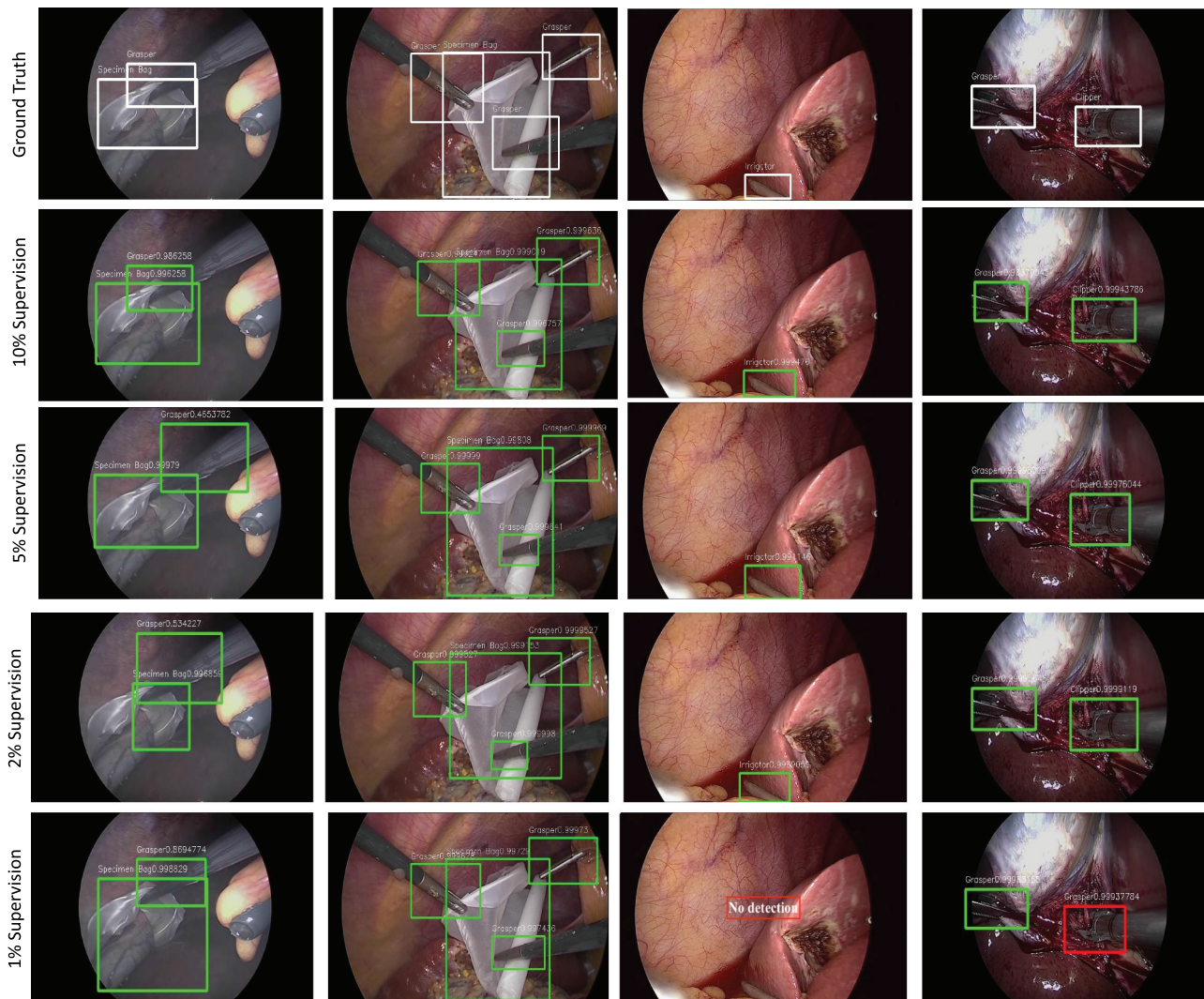
## 6. Discussion and conclusion

We demonstrate that our proposed approach performs favourably against the SOTA semi-supervised models proposed by Liu et al. (2021) and Xu et al. (2021). In 1% setting, our proposed model outperforms unbiased Teacher with focal loss by a large margin and cross entropy loss by 8 points on every evaluation metric while also outperforming SoftTeacher (Xu et al. 2021) model. It is worth noting that our approach achieves 50.632%  $mAP_{50}$  on 1% labelled data which is even higher than supervised baseline trained on 2% labelled data, and this trend can be witnessed in all settings. This improvement can be attributed to several crucial factors such as gradual improvement in pseudo label quality through EMA training which is in contrast to previous approaches in which Teacher model is frozen after

training on labelled data. Another factor is the introduction of loss function which effectively increases the foreground–background distance and helps in improving detection performance.

Furthermore, the proposed framework performs much better on  $mAP_{75}$  in all settings consistently which indicates improved localisation performance. On the 2% labelled data setting, our model obtained 72.341%  $mAP$  on 50% IoU thresholds, while unbiased Teacher on focal and cross entropy losses achieved 71.608% and 72.416% which is just slightly greater than our model. However, if we compare the performance of our model on  $mAP$  at 50:95 and 75 IoU thresholds, we observe that our model consistently gives superior performance. Moreover, on 5% and 10% setting, Unbiased Teacher (Liu et al. 2021) with focal loss achieves slightly higher performance on





**Figure 4.** Qualitative results: First row shows images with ground truth. Second, third, fourth and fifth rows present results on 10%, 5%, 2% and 1% setting, respectively. Green and red boxes indicate correct and wrong predictions.

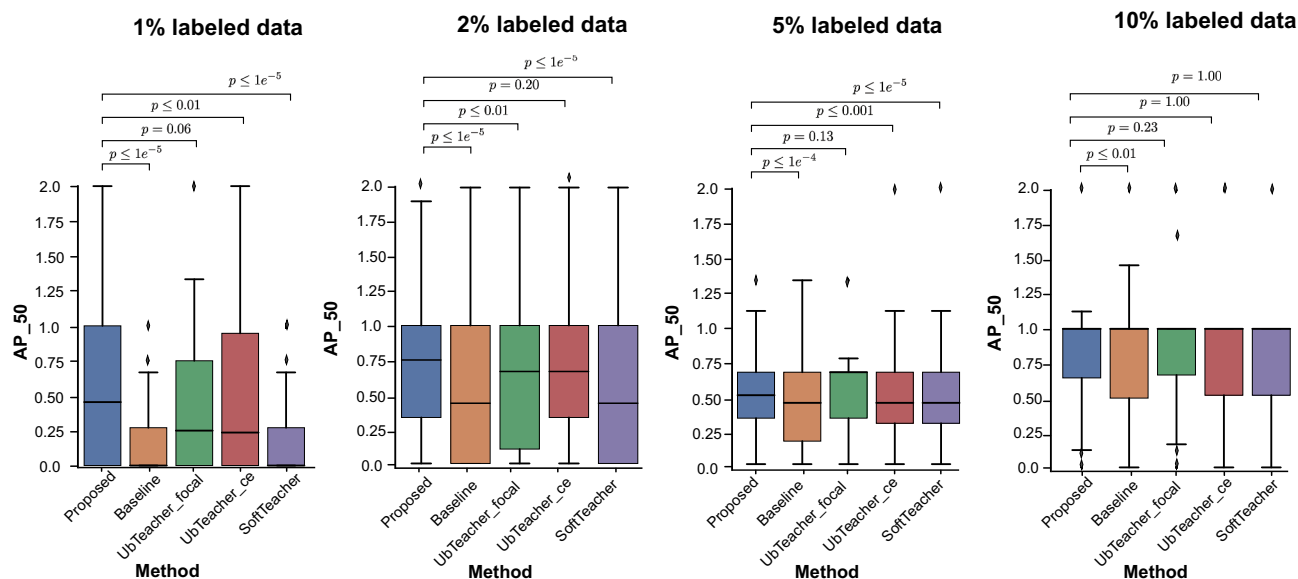
$mAP_{50}$ , but the proposed method gives superior performance in terms of  $mAP_{50:95}$  and  $mAP_{75}$ . This validates the effectiveness of our method on both classification and localisation performance. We also present per class AP ( $AP_{50:95}$ ) in Table 2. Here, we observe a significant improvement in AP on all instances, especially hard-to-detect classes like Specimen Bag (20 points), Irrigator (6 points) and Bipolar (16 points) against the supervised baseline.

The qualitative results also indicate strong performance of our approach as most of the tools (even when four tools in one frame) are detected and localised correctly. The localisation accuracy increases as we add more labelled data as is evident from Figure 4 from bottom to top; however, the detection performance remains largely unchanged. There are some missed detections on 1% of the labelled data setting (see row 5 in column 3) and incorrect class label prediction (see row 5 in column 4). The missed detection occurred mostly on 1% labelled data setting where model did not see enough annotated examples. Incorrect class prediction in the bottom right may be due to less discriminative features between both instances. Similarly, the missed detection in second last image

on the bottom row can be because the tool was only partly visible.

The paired  $t$ -test  $p$ -values computed between the proposed method and SOTA methods are given in Table 1. Also, we have shown a bar-plot with median and deviations and significance between the SOTA and proposed methods (see Figure 5). We can observe that our proposed approach performs well on different data settings. From Figure 5, it can be observed that for 1% setting our method is significantly different compared to other SOTA methods with the highest median  $AP_{50}$  value reported. Similarly, on the 2% setting, our model and Unbiased Teacher model on cross entropy loss (UbTeacher\_ce) performed equally well ( $p$ -value = 0.20) but still with the highest median value compared to other methods. Similar performance changes can be observed for 5% data where Unbiased Teacher model on focal loss (UbTeacher\_focal) has  $p$ -value = 0.13 (computed at  $AP_{50}$ ), while on  $mAP_{75}$  our method is still better. The reason behind competitive scores in these cases is because the reported APs are only done at 50% IoU threshold, while it is evident from





**Figure 5.** Box-plots for paired t-test on 1%, 2%, 5% and 10% labelled data setting. Here, the AP<sub>50</sub> scores above 1 are only shown to represent standard deviation in the scores.

Table 1 that our method performance for other mAPs at higher IoU thresholds has distinguishable improvements. However, with the 10% labelled data setting, we reach non-significant difference in  $p$ -values for other unbiased models and SoftTeacher model. This is because 10% in this case is enough data for supervision during training.

In this paper, we addressed a lack of annotated data problem in surgical domain for the first time by proposing a knowledge distillation framework. We tackle a multi-label, multi-class detection problem by implementing an end-to-end Teacher–Student learning with a multi-class foreground–background distance loss. We used strong and weak augmentation strategies to improve model robustness and class-wise NMS and EMA to improve pseudo label quality. Our experiments on m2cai16-tool dataset show the effectiveness of our model in terms of mAP on various supervision protocols against SOTA semi-supervised models. We also conducted extensive ablation experiments to demonstrate the validity of our proposed framework.

## Endnotes

1. See: <http://camma.u-strasbg.fr/datasets>

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## Disclosure statement

No potential conflict of interest was reported by the authors.

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