IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING

Confidence-Aware Paced-Curriculum Learning by Label Smoothing for Surgical Scene Understanding

Mengya Xu[®], Mobarakol Islam[®], Ben Glocker[®], and Hongliang Ren[®], Senior Member, IEEE

Abstract—Curriculum learning and self-paced learning are the training strategies that gradually feed the samples from easy to more complex. They have captivated increasing attention due to their excellent performance in robotic vision. Most recent works focus on designing curricula based on difficulty levels in input samples or smoothing the feature maps. However, smoothing labels to control the learning utility in a curriculum manner is still unexplored. In this work, we design a paced curriculum by label smoothing (P-CBLS) using paced learning with uniform label smoothing (ULS) for classification tasks and fuse uniform and spatially varying label smoothing (SVLS) for semantic segmentation tasks in a curriculum manner. In ULS and SVLS, a bigger smoothing factor value enforces a heavy smoothing penalty in the true label and limits learning less information. Therefore, we design the curriculum by label smoothing (CBLS). We set a bigger smoothing value at the beginning of training and gradually decreased it to zero to control the model learning utility from lower to higher. We also designed a confidenceaware pacing function and combined it with our CBLS to investigate the benefits of various curricula. The proposed techniques are validated on four robotic surgery datasets of multiclass, multi-label classification, captioning, and segmentation tasks. We also investigate the robustness of our method by corrupting validation data into different severity levels. Our extensive analysis shows that the proposed method improves prediction accuracy and robustness. The code is publicly available at https://github.com/XuMengyaAmy/P-CBLS.

Note to Practitioners—The motivation of this article is to improve the performance and robustness of deep neural

Manuscript received 4 July 2022; revised 20 November 2022; accepted 11 April 2023. This article was recommended for publication by Associate Editor H. Choi and Editor L. Zhang upon evaluation of the reviewers' comments. This work was supported in part by the National Key Research and Development Program of China from the Ministry of Science and Technology (MOST) of China under Grant 2018YFB1307700 and Grant 2018YFB1307703, in part by the Hong Kong Research Grants Council (RGC) Collaborative Research Fund under Grant CRF C4026-21GF, in part by the Shun Hing Institute of Advanced Engineering (SHIAE Project BME-p1-21) from The Chinese University of Hong Kong (CUHK) under Grant 8115064, in part by the General Research Fund under Grant GRF 14216022, and in part by the Shenzhen-Hong Kong-Macau Technology Research Programme (Type C) STIC SGDX20210823103535014 under Grant 202108233000303. (*Mengya Xu and Mobarakol Islam are co-first authors.*) (*Corresponding author: Hongliang Ren.*)

Mengya Xu and Hongliang Ren are with the Department of Biomedical Engineering, National University of Singapore, Singapore 119077, also with the Department of Electronic Engineering, The Chinese University of Hong Kong, Hong Kong, SAR, China, and also with the National University of Singapore (Suzhou) Research Institute (NUSRI), Suzhou 215000, China (e-mail: mengya@u.nus.edu; hlren@ieee.org).

Mobarakol Islam and Ben Glocker are with the BioMedIA Group, Imperial College London, SW7 2BX London, U.K. (e-mail: mobarakol@u.nus.edu; b.glocker@imperial.ac.uk).

This article has supplementary material provided by the authors and color versions of one or more figures available at https://doi.org/10.1109/TASE.2023.3276361.

Digital Object Identifier 10.1109/TASE.2023.3276361

networks in safety-critical applications such as robotic surgery by controlling the learning ability of the model in a curriculum learning manner and allowing the model to imitate the cognitive process of humans and animals. The designed approaches do not add parameters that require additional computational resources.

Index Terms—Surgical scene understanding, computer vision for medical robotics, deep learning methods, medical robots.

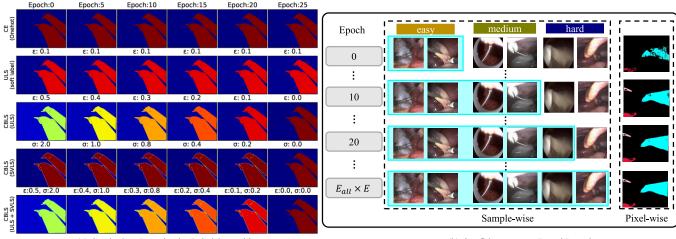
I. INTRODUCTION

S URGICAL scene understanding ability acquired with the help of deep neural networks (DNNs) is essential for developing ambient clinical intelligence. It allows for intraoperative assistance and postoperative analysis and ensures effective treatment. Despite the high performance of deep neural networks (DNNs), poor generalization, less robustness, and miscalibration issues have limited their use in safety-critical applications such as robotic surgery, medical diagnosis, and autonomous driving. The model performance often degrades with the distribution shift arising from images such as domain shift, population shift, and acquisition shift [1], [2], [3]. There are also studies to present the miscalibration of the DNNs where model prediction is overconfident and less trustworthy [4], [5]. These lead to an emphasis on designing a more robust and generalized model to provide safe and reliable predictions in sensitive applications.

Recently, curriculum learning [6] and self-paced learning [7] have attracted the interest of people in machine learning and computer vision due to their outstanding generalization ability. Both learning paradigms are based on the learning principle that underpins the cognitive process of humans and animals, ordering samples based on their difficulty levels during the model training. Several studies have observed that curriculum learning can significantly improve the generalization and convergence speed in computer vision [8], [9], [10], [11] and natural language processing [12]. The performance of curriculum learning mostly depends on how accurate is the difficulty measurement technique. Most previous works have used confidence-based difficulty scores from a baseline model [13], [14]. Handcrafted features [15], annotator agreement [16], and similarity scores [17] are also utilized to sort the samples from more uncomplicated to more complex. Most recently, Sinha et al. [18] apply Gaussian smoothing from higher to lower gradually on the feature maps to control information flow during training. However, all these works either focus on input samples or feature maps to design the curriculum scheme without considering the adjustment of learning utility through label smoothing.

1545-5955 © 2023 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See https://www.ieee.org/publications/rights/index.html for more information.

IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING



(a) Curriculum Learning by Label Smoothing

(b) Confidence-aware Paced Learning

Fig. 1. **Confidence-Aware Paced-Curriculum Learning by Label Smoothing** (a) Curriculum Learning by Label Smoothing. one-hot for cross-entropy (CE) and smoothed labels for uniform label smoothing (ULS) and various CBLS versions over the training epochs. The different colors of the instrument area displayed in the label map reflect different smoothing factor values. CE (one-hot) sets the smoothing factor ϵ to 0. Thus the instrument area is always dark red over the training epochs. ULS (soft label) set ϵ to 1. The instrument area keeps rose red with training. Our CBLS contains three different versions: ULS, SVLS, and ULS+SVLS. As training progresses, we decrease the smoothing factor of ULS (ϵ), SVLS (σ), and ULS+SVLS (ϵ and σ) gradually to squeeze the label in a curriculum way that changes the true probability value from lower to higher. In the label map of CBLS (ULS), the instruments area contour is the same as the interior color. In the label map of CBLS (SVLS), the smoothing factor ϵ of ULS nemains at 0, and the smoothing factor σ of SVLS decreases gradually. σ mainly affects the value at the contour. Therefore, the color of the instrument contour is also different from the interior color. However, the interior color is also gradually changing as the smoothing factor ϵ of ULS decreases. (b) Confidence-aware Paced Learning, including sample-wise paced learning, and pixel-wise paced learning. The samples or pixels are chosen in the order of easier to harder levels based on their confidence score during training.

In this work, we explore label smoothing [19], a regularization method that can penalize the over-confidence prediction [20] by flattening the hard targets into the soft labels, to design Curriculum By Label Smoothing (CBLS). We utilize three variations of label smoothing, (i) uniform label smoothing (ULS) [19], (ii) spatially varying label smoothing (SVLS) [21], and (iii) fused ULS and SVLS to develop our CBLS. We vary the smoothing factor from higher to lower over the training epochs to flatten the hard target (one-hot) to control learning utility in a curriculum manner. Fig. 1(a) demonstrates the hard label and soft labels for different learning strategies such as cross-entropy (CE), ULS, proposed CBLS (ULS), CBLS (SVLS), and CBLS (ULS + SVLS). We also design a confidence-aware pacing function (see Fig. 1(b)) to conduct extensive analysis between different types of curriculum techniques and their individual and combined benefits. Our main contributions are summarized as follows:

- We design a novel curriculum learning strategy, Curriculum By Label Smoothing (CBLS), by smoothing labels in a curriculum manner that controls the learning utility from lower to higher;
- We develop a confidence-aware pacing function to order from easy to more complex samples for classification tasks and pixels for segmentation tasks and build paced-CBLS (P-CBLS) to investigate the benefits of both curricula;
- Our method shows improved performance over multiple baselines for four robot vision recognition tasks of multi-class, multi-label classification, captioning, and segmentation;

• We also investigate the robustness of CBLS by corrupting images with different severity levels, and the results suggest the constantly improved prediction with the severity increases.

II. RELATED WORK

A. Curriculum Learning / Self-Paced Learning

Inspired by human and animal learning principles, curriculum learning introduces samples from easier to the complex during training. It is observed that the learning process from easy to difficult tasks helps achieve better performance by avoiding the local minima and obtaining better generalization results [22], [23]. Curriculum learning and selfpaced learning also improve the robustness and reliability of noisy samples [9], [11]. There are several ways to measure the sample difficulty in designing this learning technique. Most of the works adopt the confidence score to sort the samples. In this way, first, feed the high confidence/easy samples and subsequently introduce low confidence/difficult ones into the learning. Previous studies also utilized handcrafted features [15], multi-raters disagreement [16] and similarity scores [17]. A cutting-edge strategy [24] is introduced to use curricula to pinpoint the fundamentals of how a system learns. Domain-aware Curriculum Learning [25] identifies curriculum learning as one crucial element that can reduce the multiple domain shifts in the multi-target domain adaptation. It adapts to the easier target domains first, then moves on to the more difficult ones. A curriculum based on human visual acuity [26] lessens the texture biases in models for gallbladder cancer. Most recently, the Curriculum By Smoothing (CBS) [18]

employs the Gaussian filter of feature maps from a higher variance to lower across the training epochs. The higher variance smoothes the feature map heavily and limits the model to learn less information at the beginning. However, designing a curriculum by smoothing label probability is still unexplored in this domain.

B. Label Smoothing

Label smoothing is originally proposed by [19] as a learning strategy to improve the prediction. We name it uniform label smoothing (ULS) in our work. Many classification models [27], [28], [29] incorporate ULS as the regularization technique to improve the model learning. Most recently, ULS has been found to be a calibration technique that limits the overly-confidence prediction by flattening full probability in the hard targets [20]. There is also evidence that ULS can improve the feature representation and boosts the performance of the feature extraction models [30], [31]. However, a study demonstrates that constant label smoothing lowers the utility of DNNs by degrading their refinement performance [32]. Another study presents that ULS is incompatible with the semantic segmentation task and proposes spatially varying label smoothing (SVLS) [21] to confirm spatial variation among class regions. In this work, we adopt ULS and SVLS to control the learning utility as a curriculum scheme.

C. Robustness

The vast majority of research on robustness in for vision has focused on the critical issues of robustness to adversarial examples [33], [34], [35], unknown unknowns [36], and data poisoning [37]. Benchmark datasets for two other forms of robustness (corruption and perturbation) are developed to test the robustness of a classifier [38]. The robustness enhancement is proved and validated on a diverse test set that contains the corrupted and perturbed images [39], [40]. In this work, we utilize the corruption and perturbation techniques to create a new test dataset to validate the robustness of our method.

III. BACKGROUND AND PRELIMINARIES

Uniform label smoothing (ULS) Label smoothing (LS) is a regularization technique that improves the generalization and learning efficiency of DNNs by replacing one-hot labels with smoothed labels. It uniformly flattens the one-hot label ($T_{one-hot}$) by using a smoothing factor. Therefore we call it Uniform Label Smoothing (ULS) in this work. In $T_{one-hot}$, true class represents with "1" and the rest with "0". Then the smoothed label (soft label) T_{ULS} is represented as

$$T_{ULS} = T_{one-hot}(1-\epsilon) + \epsilon/K \tag{1}$$

where the number of classes K, the smoothing factor ϵ range of (0, 1) that decides smoothing strength and is always kept as a constant with training, as shown in Fig. 2.

Spatially varying label smoothing (SVLS) LS smoothes the label uniformly, which is not compatible with semantic segmentation. Spatially Varying Label Smoothing (SVLS) [21] is a soft labeling technique that captures the ambiguity and uncertainty about object boundaries in expert segmentation annotation. SVLS determines the probability of the target class based on neighboring pixels by designing an SVLS weight matrix, w^{svls} , with a Gaussian kernel $k(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{|\vec{x}|^2}{2\sigma^2}}$ with smoothing factor σ set to 1. SVLS weight matrix is convolved across the one-hot encoding targets to obtain soft class probabilities, as shown in the equation below.

$$T_{SVLS} = w_{svls}(\sigma) \circledast T_{one-hot}$$
(2)

Similar to ULS, SVLS smoothing factor is also used to control smoothing strength and is kept constant during training. Changing the smoothing factor in a curriculum manner is still an unexplored area.

Self-paced learning Self-Paced Learning (SPL) [11] incorporates a self-paced function f(v) and a pace parameter γ into the standard loss function. The total loss can be formulated as $\mathcal{L}_{total} = \sum_{i=1}^{n} (v_i \mathcal{L}(t_i, y) + \gamma f(v))$. The standard loss $\mathcal{L}(t_i, y)$ calculates the loss between the ground truth target t_i and the predicted target y. The self-paced function is used to learn the weight variable v, which indicates whether the samples are easy or not. When pace parameter γ is small, only "easy" samples with small losses are introduced into the training. As γ increases, more "difficulty" samples with large loss are appended into training.

The weight variable v [11] is dynamically updated during training. In our work, we implement confidence-aware paced learning based on the pre-decided samples bank.

IV. PACED-CURRICULUM LEARNING BY LABEL SMOOTHING (P-CBLS)

In this work, we design Paced-Curriculum by Label Smoothing (P-CBLS) using paced learning with ULS [19] and SVLS [21] in a curriculum manner, as shown in Fig. 1. We build the confidence-aware sample bank sorted by sample difficulty and decrease the smoothing factors of ULS (ϵ) and SVLS (σ) gradually to squeeze the label in a curriculum way where true probability value is modified from lower to higher during training epochs. It is worth noting that the proposed P-CBLS adds no additional trainable parameters, is generic, and can be used with any DNNs variant. Our novelty also lies in the task difficulty measurement strategy of samplelevel difficulty and pixel-level to better cope with different task scenarios. Moreover, the investigation of the robustness of our P-CBLS helps to improve the generalization of the deep neural network. P-CBLS is described in more detail in the following sections.

A. Curricula in ULS

We design curricula in Uniform Label Smoothing (ULS) which aims to exponentially decrease the smoothing factor ϵ^c during training where higher values flatten the true probability heavily and reduce the learning utility. Therefore the model learns less information at the beginning epochs and gradually learns more information. The curriculum strategy is designed to anneal the smoothing factor ϵ^c with a decay rate of α ($\alpha < 1$) in every epoch during the training, as demonstrated in Fig. 2. The attenuation of the smoothing factor can be

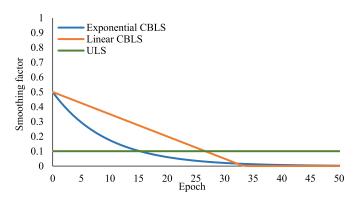


Fig. 2. Illustration of ULS vs. Exponential CBLS vs. Linear CBLS. The smoothing factor ϵ exponentially decreases in Exponential CBLS and linearly decreases in Linear CBLS. In ULS, the smoothing factor keeps constant.

implemented by using exponential or linear decrease. And we refer to them as exponential Curriculum by Label Smoothing (CBLS) and linear CBLS, respectively. Compared with linear CBLS, the smoothing factor of exponential CBLS decays more smoothly.

From Equation 1, the curriculum smoothed target T_{ULS}^c is formulated as

$$T_{ULS}^{c} = T_{one-hot}(1 - \epsilon^{c}) + \epsilon^{c}/K$$
(3)

where, curriculum smoothing factor $\epsilon^c = \alpha \epsilon^c$ and smoothing decay rate α .

If *P* is the predicted probability, then the CE loss with the curriculum smoothed target T_{ULS}^c can be present as

$$\mathcal{L}_{CE}^{c} = -\sum_{i=1}^{K} T_{ULS(i)}^{c} log(P_{(i)})$$
(4)

B. Curricula in SVLS

We design a curriculum in Spatially Varying Label Smoothing (SVLS), decreasing boundary uncertainty in segmentation labels. For this purpose, we decrease the SVLS smoothing factor σ from a higher to lower value over the training epoch to ensure less information to learn at the beginning of training and gradually increase the learning utility.

From Equation 2, the curriculum smoothed target T_{SVLS}^c is formulated as

$$T_{SVLS}^{c} = w_{svls}^{c}(\sigma^{c}) \circledast T_{one-hot}$$
⁽⁵⁾

where, curriculum SVLS weight matrix $w_{svls}^c(\sigma^c)$, smoothing factor $\sigma^c = \beta \sigma^c$ and smoothing decay rate β .

C. Curricula in ULS and SVLS

We design to implement the curricula in ULS and curricula in SVLS simultaneously. The curriculum smoothed target $T_{ULS+SVLS}^{c}$ is formulated as

$$T_{ULS+SVLS}^{c} = w_{svls}^{c}(\sigma^{c}) \circledast T_{ULS}^{c}(\epsilon^{c})$$
(6)

where, σ^c and ϵ^c are the curriculum smoothing factors for ULS and SVLS. The main difference between Equation 5 and Equation 6 is, w_{svls}^c does convolution operation with T_{ULS}^c

rather than with $T_{one-hot}$. Fig. 1 (a) shows an overview of labels and soft labels over the epochs for different training strategies where one-hot encoding label $T_{one-hot}$, ULS soft label T_{ULS}^c , SVLS soft label T_{SVLS}^c and fused ULS & SVLS soft label $T_{ULS+SVLS}^c$ in curricula manner.

D. Confidence-Aware Paced Learning

To make sure easier information to train first, we design confidence-aware paced learning where harder samples are skipped at the beginning of the training and gradually introduced in later epochs. This is achieved by sorting the sample based on the confidence score from the baseline model to build a sample bank. A sample with high confidence score can be interpreted as the easier sample, and a sample with a low confidence score is a harder sample in the curriculum learning. The obtained easy samples and difficult samples are visualized in Fig. 1 (b). To incorporate paced learning into curricula, we tune hyperparameters of the ratio of initial easy samples and ratio of epoch to introduce all the training samples. If the initial sample ratio λ , which is the ratio of initial sample size and the total number of samples when we start the training, the number of total epochs E, the epoch ratio E_{all} which is the ratio of the epoch when introducing all training samples and the total epochs E, then the pace parameter μ (ratio of additional harder samples per epoch) can be formulated as

$$\mu = \frac{1.0 - \lambda}{E_{all} \times E} \tag{7}$$

In our experiments, we tune the initial sample ratio λ and the epoch ratio E_{all} to determine the pace parameter μ . Our sample ratio λ plus pace parameter μ have a similar meaning with the pace parameter γ in [11].

To build our sample bank, we can sort the sample in two different techniques by utilizing the confidence score.

- Sample-wise In sample-wise sorting, we can measure the confidence score for each sample and sort them from easy (higher confidence) to difficult (lower confidence). This can be applicable to multi-class classification and segmentation tasks. For multi-label classification, we take the average confidence of all instances in a sample and then sort all the samples based on averaged confidences, as shown in Fig. 1 (b) (Sample-wise).
- **Pixel-wise** Pixel-wise sample bank is only compatible with semantic segmentation task. The semantic segmentation task can be modeled as the dense pixel classification problem. Therefore, the sample bank can be constructed in pixels. In a pixel-wise sample-bank, we calculate the confidence of each pixel and sort them from easy to difficult pixels, as shown in Fig. 1 (b) (Pixel-wise).

The details of calculating the sample-wise score for different tasks are

- Workflow Classification The sample-wise confidence score is obtained from the predicted probability of the true class.
- **Tool Classification** The sample-wise confidence score is obtained by averaging the predicted probability of true classes. For the frames with no instrument, we average

the predicted probability for all classes, which is a low value.

- Tool Segmentation The frame with no instrument has no learning value for the instrument segmentation task. Thus, the confidence score for such a frame is set to 0 directly. For the frame with instruments, we calculate the predicted probability of the true foreground classes and do the average for them. The background classes are not considered.
- **Surgical Captioning** The sample-wise confidence score is obtained by averaging the predicted probability of true classes.

E. P-CBLS

We take our sample-wise P-CBLS (ULS) as an example to illustrate the algorithm of P-CBLS in Algorithm 1. Our proposed P-CBLS consists of CBLS, and confidence-aware paced learning. In CBLS, we decrease the smoothing factor ϵ^{c} in a curriculum way every epoch. It can be formulated as $\epsilon^{c} = \alpha \epsilon^{c}$, where the decay rate α . Meanwhile, confidenceaware paced learning is incorporated. Specifically, the model parameter w is updated every epoch. The model is trained with partial samples of size $L = \lambda \times N$ at the beginning, where the sample ratio λ . The sample size used to train the model increases by $(\mu \times e) \times N$ every epoch before the $(E_{all} \times E)$ th epoch, where the total size of samples N, the pace parameter μ , the total epochs E, and the epoch ratio E_{all} . When current epoch *e* reaches the $(E_{all} \times E)$ th epoch, the smoothing factor ϵ^{c} is still being decayed, and the model is trained with all samples of size Nuntil we complete the total epochs E.

Algorithm 1 Algorithm of Sample-Wise P-CBLS (ULS)

1: **Input:** The training dataset of varying size *L*, the total number of samples *N*, the sample ratio λ , the pace parameter μ . the total epochs *E*, the epoch ratio E_{all} , current epoch *e*, smoothing factor ϵ^c , decay rate α ($\alpha < 1$)

2: **Output:** Model parameter w

3: **Training** Initialize w^*

The initial training size $L = \lambda \times N$ If $e < (E_{all} \times E)$ Then: $L = (\lambda + \mu \times e) \times N$ $\epsilon^c = \alpha \epsilon^c$ Update w^* Else L = N $\epsilon^c = \alpha \epsilon^c$ Update w^* return $w = w^*$

We hope Algorithm 1 helps to differentiate our approach from the CBS [18] approach. Our P-CBLS approaches depart from CBS [18] with several points: (1) The designed curricula are different where CBS [18] is designed based on feature smoothing and proposed CBLS is designed based on label smoothing. CBS [18] is focused on designing curricula based on smoothing the feature maps by adjusting the standard deviation δ of the Gaussian kernels. The information is gradually added, which leads to improvement in feature maps which Convolutional Neural Networks (CNNs) learn from. Our CBLS and P-CBLS smooth labels control the learning utility in a curriculum manner, which is an unexplored area. (2) Our P-CBLS approach further integrates sample-wise confidence-aware paced learning into CBLS (ULS) for the classification task and fuse pixel-wise confidence-aware paced learning and CBLS (SVLS) for the segmentation task. (3) The scope of experiments is different. CBS [18] is evaluated on the image classification task. Our approaches are evaluated for tasks ranging from image understanding tasks (multiclass workflow classification, multi-label tool classification, and segmentation) to the caption generation task. We also evaluate the robustness of our approaches.

V. EXPERIMENTS

A. Dataset

M2CAI16-Workflow Classification is a public challenge dataset from MICCAI 2016 modeling and monitoring of computer-assisted interventions challenge [41]. The training dataset includes 27 videos about cholecystectomy surgery. These videos are acquired at 25fps and segmented into 8 phases. 7 videos from the training set are split as the validation set (18723 labeled frames), and the rest videos are split as the training set (48854 labeled frames). Each frame has a resolution of 1920 × 1080. We resize these frames into 250×250 following the work [42].

MICCAI17/18-Tool Classification is a tool detection dataset built from the publicly available dataset MICCAI robotic instrument segmentation challenge 2017 [43] and 2018 [44]. We extract the instrument labels from segmentation annotation from these datasets. To maintain balance classes, the dataset is split into 1560/1244 images for train and validation. The images are resized to 224×224 , and multiple instances can be present in an image with 8 tool classes.

Tool Segmentation experiments are also conducted with MICCAI robotic instrument segmentation 2018 [44]. A typewise segmentation annotation is used in this work by following [45]. The validation set includes the 2^{nd} , 5^{th} , 9^{th} , and 15^{th} sequences (596 labeled frames). The training set includes the remaining sequences (1639 labeled frames). The frames are resized into half from the original resolution of 1024×1280 .

Surgical Captioning is also generated from the MICCAI robotic instrument segmentation challenge 2018 [44]. The original training set includes 15 robotic nephrectomy operations obtained by the da Vinci X or Xi system. Each video sequence includes 149 frames with a resolution of 1024×1280 . After removing the 13^{th} sequence due to the fewer surgical activities, we split the training set (14 sequences) into two subsets following [31], [46]. The validation subset includes 1^{st} , 5^{th} , 16^{th} sequences (447 labeled frames). The training subset includes the remaining sequences (1560 labeled frames). The caption annotation is taken from [46].

6

IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING

B. Experiments and Results

In this section, we refer to a model trained with the standard way (i.i.d.) with cross-entropy (CE) loss and label smoothing as baseline and LS, respectively. Our method can be presented as CBLS (ULS), and CBLS (SVLS) based utilizing curriculum techniques using uniform LS and spatially varying LS. Both our variants can integrate with confidence-aware paced learning and refer to as P-CBLS (ULS) or P-CBLS (SVLS). We tune the hyper-parameters of the smoothing factor, decay, and initial pacing parameter and choose the best value for further experiments. We set smoothing factor ϵ of 0.1 for all the LS experiments to maintain fair comparison. As the pacing function forms from the confidence score of the baseline, we calibrate the baseline using a well-known calibration technique, temperature scaling [4].

1) Classification: We adopt two popular classification architectures ResNet50 [47], and DenseNet121 [48], for multiclass and multi-label classification datasets of robot-assisted surgical workflow [41] and tool classification [43], [44]. Multi-class workflow classification dataset trains on SGD optimizer, momentum of 0.9, weight decay of 5e - 3, and learning rate decay of 0.1 with an initial learning rate of 5e - 3 by following [42]. On the other hand, we follow previous work [49] with the hyper-parameter setting where we use Adam optimizer with a learning rate 1e - 4 for the multi-label tool classification task. Other hyper-parameters for CBLS and P-CBLS are assigned as the initial smoothing factor of 0.5, smoothing decay of 0.9, initial sample ratio λ of 0.6, and epoch ratio for all samples E_{all} of 0.4.

The results are tabulated in Table I, where we report the accuracy for multi-class workflow classification and mean average precision (MAP) for multi-label tool classification. The proposed CBLS and P-CBLS have improved the performance by around 2% in accuracy for DenseNet121 and MAP for ResNet50. Our CBLS approach shows the best results in the workflow classification task, and our P-CBLS approach achieves the best results in the tool classification task. Both CBLS and P-CBLS are our proposed methods. For either set of experiments, we do not tune any hyperparameters. Therefore, we do not expect that P-CBLS will always get better results. The proper and suitable hyperparameters of P-CBLS, including initial sample ratio λ and epoch ratio for all samples E_{all} , may further boost the P-CBLS performance for different tasks or datasets.

2) Segmentation: For the tool segmentation task, we adopt two commonly used segmentation architectures of LinkNet34 [50], [51] and DeepLabv3+ [52] and their implementation^{*,†}. The architectures are trained on Adam optimizer with a learning rate of 1e - 4 by following [51]. The hyper-parameters for CBLS (ULS), CBLS (SVLS), and P-CBLS are the initial ULS smoothing factor ($\epsilon = 0.6$, decay = 0.9) and SVLS smoothing factor ($\sigma = 0.9$, decay = 0.5), initial pixel ratio ($\lambda = 0.8$) and epoch ratio for all samples ($E_{all} = 0.4$).

TABLE I

WORKFLOW CLASSIFICATION, TOOL CLASSIFICATION. CLASSIFICA-TION ACCURACY AND MEAN AVERAGE PRECISION (MAP) ON M2CAI16-WORKFLOW, MICCAI17/18-TOOL DATASET USING BASELINES(RESNET50 [47] AND DENSENET121 [48]), ULS (SMOOTHING FACTOR OF 0.1), AND OUR PROPOSED CBLS (ULS) AND P-CBLS (ULS). WE USE THE SAME CBLS AND P-CBLS HYPER-PARAMETERS FOR A FAIR

COMPARISON

	Model	Workflow Accuracy	Tool Class MAP
Baseline	Resnet50 [47]	68.16	54.09
Базение	LS [19]	71.48	52.88
Ours	CBLS	71.66	54.92
Ours	P-CBLS	71.76	54.75
Baseline	Densenet121	67.75	53.58
Dasenne	LS	68.65	55.42
0	CBLS	69.59	55.84
Ours	P-CBLS	70.43	55.75

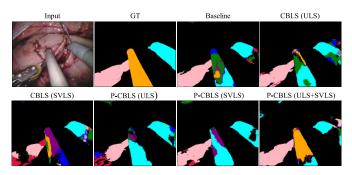


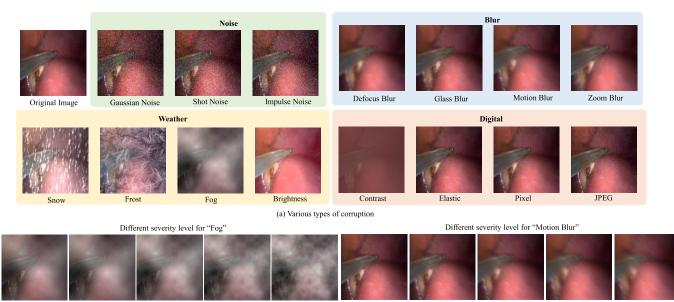
Fig. 3. Visualization of the predicted mask of LinkNet34 [50] model based on different proposed approaches. Bipolar forceps, prograsp forceps, monopolar curved scissors, and suction are indicated in pink, red, blue, and yellow. P-CBLS here specifically refers to pixel-wise paced learning.

The results are tabulated in Table II, where we report the mean IoU and mean Dice. The proposed various CBLS and P-CBLS have improved the performance at least by 3% in Dice and 1% in IoU for LinkNet34. For DeepLabv3+, the proposed methods obtain around 1% improvement in Dice. In addition to significantly improving the IoU and Dice of the baseline CE approach, we see that training both model architectures using our CBLS (SVLS) outperforms our CBLS (ULS) by a good margin. The improvement in these two metrics suggests that our CBLS (SVLS) makes models better at capturing the ambiguity about the object contours. By fusing the CBLS (ULS) and CBLS (SVLs), we can see further performance improvements. Based on these findings, we conduct the same experimental design by incorporating pixel-wise confidenceaware paced learning. For LinkNet34, P-CBLS (ULS+SVLS) obtains the best performance. In comparison, P-CBLS (ULS) attains the best performance for DeepLabv3+. We attribute it to the fact that DeepLabv3+ converges faster than LinkNet34 usually. Therefore, the selected hyper-parameters of P-CBLS in our fixed setting cannot further contribute to improving the performance of the DeepLabv3+. The predicted masks generated by our proposed models are visualized in Fig. 3. We can observe that for the "suction" instrument, which is indicated by the yellow color in Ground Truth (GT) image, the traditional CE approach fails to predict it. For the "monopolar curved scissors" instrument, which is represented

^{*}https://github.com/ternaus/robot-surgery-segmentation

[†]https://github.com/MLearing/Pytorch-DeepLab-v3-plus

XU et al.: CONFIDENCE-AWARE PACED-CURRICULUM LEARNING



severity level = 3 severity level = 3 severity level = 2severity level = 4 severity level = 5 severity level = 1 severity level = 2 severity level = 4 severity level = 5 severity level = 1(b) Different severity level

Fig. 4. Visualization of various types of corruption and different severity levels on M2CAI16 Workflow dataset. (a) Four types of corruption with severity level = 3, including noise, blur, weather, and digital, which are from the following filters "Gaussian, Shot, Impulse", "Defocus, Glass, Motion, Zoom;", "Snow, Frost, Fog, Bright", and "Contrast, Elastic, Pixel, JPEG" respectively. (b) Five different severity levels.

TABLE II

TOOL SEGMENTATION. MEAN IOU AND MEAN DICE ARE REPORTED ON THE TOOL SEGMENTATION DATASET FOR OUR CBLS VARIANTS OVER BASELINES OF LABEL SMOOTHING (LS) AND CROSS-ENTROPY (CE) LOSS USING LINKNET34 [50] AND FIX [52]

	Model		Net34	DeepLabv3+		
	Widdel	IoU Dice IoU 44.04 53.56 44.62 42.75 50.78 44.15 43.70 51.94 45.93 47.05 56.10 45.93 47.35 54.95 45.24 48.91 59.92 47.93		Dice		
	CE	44.04	53.56	44.62	54.67	
Baseline	LS [19]	42.75	50.78	44.15	53.44	
Dasenne	Online LS [53]	43.70	51.94	45.93	56.38	
	SCE [54]	47.05	56.10	45.93	54.97	
	CBLS (ULS)	47.35	54.95	45.24	54.53	
	CBLS (SVLS)	48.91	59.92	47.93	57.31	
01146	CBLS (ULS+SVLS)	50.63	61.14	47.92	55.21	
Ours	P-CBLS (ULS)	48.71	57.54	48.33	58.08	
	P-CBLS (SVLS)	53.23	64.94	45.28	55.23	
	P-CBLS (ULS+SVLS)	54.71	65.65	46.18	55.50	

by blue color in the GT image, the prediction of the CE approach is still largely wrong. Our various CBLS versions, including CBLS (ULS), CBLS (SVLS), P-CBLS (ULS), and P-CBLS (SVLS), show better performance on the "monopolar curved scissors" instrument. Our P-CBLS (ULS+SVLS) shows superior performance on the "suction" instrument.

3) Captioning: For the image to caption generation, we use Mesh-Transformer $(M2T)^{\ddagger}$ [55] and adopt the same parameters and object features from [46]. All models are evaluated using four metrics for image captioning, namely BLEU-n [56], ROUGE [57], METEOR [58], CIDEr [59]. We apply our curriculum methods on the M2T [55] and compared with the original M2T [55], X-LAN [60], and image captioning models from [31]. We use initial smoothing factor ϵ of 0.1, decay rate α of 0.95, and initial sample ratio λ of 0.9.



GT: monopolar curved scissors is cutting tissue

Baseline: prograsp forceps and monopolar curved scissors are idle LS: monopolar curved scissors is cutting tissue prograsp forceps is manipulating tissue **CBLS:** monopolar curved scissors is cutting tissue **P-CBLS:** monopolar curved scissors is cutting tissue

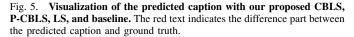


GT: monopolar curved scissors is cauterizing tissue, prograsp forceps is manipulating tissue

Baseline: clip applier is clipping tissue bipolar forceps is looping tissue LS: prograsp forceps is manipulating tissue

CBLS: clip applier is clipping tissue bipolar forceps is looping tissue

P-CBLS: monopolar curved scissors is cutting tissue bipolar forceps and prograsp forceps are manipulating tissue



The caption prediction of our curriculum-based networks is visualized in Figure 5. Our methods show superiority over other state-of-the-art methods on the M2CAI-2018 captioning dataset. As shown in TABLE III, the proposed P-CBLS has improved the performance by around 0.01 in BLEU-1 and METEOR, around 0.02 in ROUGE, and around 0.7 in CIDEr when compared with [31]. Our P-CBLS presents better performance on BLEU-4, ROUGE, and CIDEr.

C. Robustness

A more quantitative approach for analyzing the robustness of a model is its response to manually generated corruption

[‡]https://github.com/aimagelab/meshed-memory-transformer

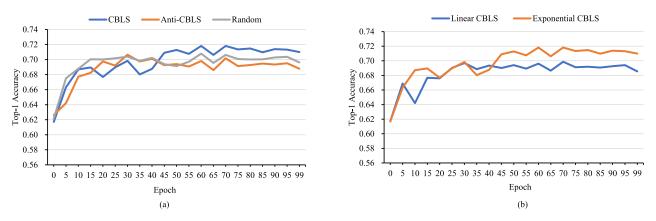


Fig. 6. Different training paradigms to change the smoothing factor with ResNet50 on the M2CAI16-Workflow dataset. (a) CBLS vs. Anti CBLS vs. Random. (b) Exponential CBLS vs. Linear CBLS.

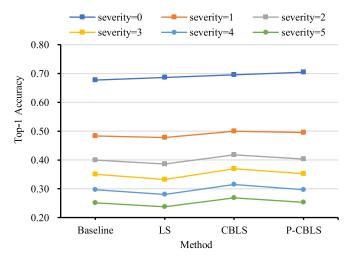


Fig. 7. **Robustness performance**. Performance of DenseNet121 for our CBLS and P-CBLS compared to baselines across various severity levels of corruption on the Workflow classification dataset.

TABLE III

SURGICAL CAPTIONING. BLEU-N [56], METEOR [58], ROUGE [57] AND CIDER [59] ON THE SURGICAL CAPTIONING DATASET FOR NETWORK ARCHITECTURE TRAINED NORMALLY, TRAINED USING ULS WITH SMOOTHING FACTOR OF 0.1, AND TRAINED USING OUR PROPOSED CBLS AND P-CBLS. COMPARED WITH BASELINE ARCHITECTURES: X-LAN [60], XU ET AL. [46], M2T [55], WE SHOW SIGNIFICANT IMPROVEMENTS USING OUR PROPOSED METH-ODS BASED ON THE M2T [55]

I	Model	BLEU-4	METEOR	ROUGE	CIDEr
	X-LAN [60]	38.85	34.84	56.42	205.99
Baseline	Xu et al [46]	44.52	35.32	60.17	265.24
	M2T [55]	42.29	35.67	58.95	274.78
	LS (M2T)	46.21	35.45	60.53	296.04
Ours	CBLS	45.07	36.52	60.25	309.65
Ours	P-CBLS	47.46	35.67	62.63	340.67

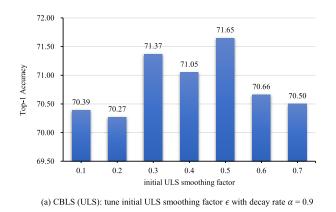
and perturbation to the images [40]. Therefore, we design four types of corruption, including noise, blur, weather, and digital, which are from the following filters "Gaussian, Shot, Impulse", "Defocus, Glass, Motion, Zoom", "Snow, Frost, Fog, Bright", and "Contrast, Elastic, Pixel, JPEG" respectively to validate the robustness performance of the baselines, and our proposed CBLS and P-CBLS, as shown in Fig. 4. When the model is more robust to corruption and perturbation, it will show higher accuracy. As the severity increases, if the model can preserve performance, then it can be regarded as more robust [38]. Results are demonstrated in TABLE IV. Our approaches obtain competitive results overall. Although CBLS yields 0.5, 0.6, and 0.2 lower than the baseline for Blurred-Glass, Blurred-Motion, and Weather-Fog, our CBLS and P-CBLS significantly outperform most corruption types. In our experiments, each corruption type integrates 5 different corruption severity levels. For Blurred-Glass, Blurred-Motion, Weather-Fog, overhigh corruption severity levels may make the image deviate too much from the original image, which makes the corrupted image illegible. Our approach aims to control the model learning utility from lower to higher in the curriculum manner. Compared to the baseline, our approaches may be more sensitive to such corruption types, which causes too much deviation from the original image because the model with only a lower learning utility in the early stages of training may face frustration when encountering such indistinguishable and difficult images. We also plot the performance degradation over the five severity levels of the corruption in Fig. 7. The results suggest that LS and baseline are remarkably degraded with the increase in severity, whereas CBLS preserves better performance.

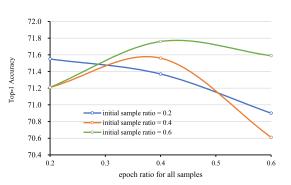
D. Ablation Study

1) Curriculum vs. Anti-Curriculum vs. Random: We design three different training paradigms to change the smoothing factor: **CBLS** (initial ULS smoothing factor of 0.5, the decay rate of 0.9. The minimum of ULS smoothing factor is restricted to 0), **Anti-CBLS** (initial ULS smoothing factor of 0.005, the decay rate of 1.1. The maximum of ULS smoothing factor is restricted to 0.5) and **Random** (ULS smoothing factor is from the random value within the range of (0, 0.5) during training) on M2CAI16-Workflow dataset, to demonstrate the superiority of our CBLS approach. The results are shown in Fig. 6 (a). It is interesting to see that Anti-CBLS performs worse than CBLS and the random way to choose the smoothing factor.

2) Exponential CBLS vs. Linear CBLS: We study the attenuation of smoothing in an exponential way (initial ULS smoothing factor of 0.5, decay rate of 0.9) and a linear

XU et al.: CONFIDENCE-AWARE PACED-CURRICULUM LEARNING





(b) P-CBLS (ULS): tune initial sample ratio and epoch ratio for all samples E_{all} with ULS smoothing factor $\epsilon = 0.5$, decay rate $\alpha = 0.9$

Fig. 8. Ablation study of the hyperparameters of our proposed approaches on the M2CAI16 Workflow Classification dataset with ResNet50 model. (a) hyperparameters of CBLS. (b) hyperparameters of P-CBLS.

TABLE IV

PERFORMANCE OF OUR CBLS AND P-CBLS OVER BASELINES UNDER VARIOUS TYPES OF CORRUPTION ON M2CA116 WORKFLOW DATASET WITH DENSENET121. THE RESULTS ARE OBTAINED FROM FIVE DIFFERENT SEVERITY LEVELS AND AVERAGE THEM FOR EACH CORRUPTION

		Noise			Bl	ur			Wea	ather			Digita	al		Mean
Model	Gauss.	Shot	Impulse	Defocus	Glass	Motion	Zoom	Snow	Frost	Fog	Bright	Contrast	Elastic	Pixel	JPEG	wican
Baseline	32.5	33.6	29.3	37.4	41.9	42.6	42.8	29.4	32.5	43.0	53.5	33.8	55.7	58.2	48.8	41.0
LS	30.7	31.4	30.8	34.2	38.8	38.7	43.6	26.4	29.8	42.2	54.7	36.9	55.5	58.4	48.2	40.0
CBLS	33.8	34.8	31.4	37.7	41.4	42.0	47.8	32.4	33.3	42.8	57.6	38.4	57.5	60.8	50.0	42.8
P-CBLS	35.0	35.7	32.3	38.3	40.0	41.4	44.8	28.6	27.7	42.0	55.2	37.5	57.5	57.9	52.6	4.18

way (initial ULS smoothing factor of 0.5, decay rate of 0.015) on the M2CAI16-Workflow dataset. And we refer to them as Exponential CBLS and Linear CBLS, respectively. We observed that the Exponential CBLS outperforms Linear CBLS by a large margin, as demonstrated in Fig. 6 (b). We also show the comparison between exponential CBLS and linear CBLS based on the Tool Segmentation dataset, as demonstrated in TABLE VI. Exponential CBLS has better performance than linear CBLS.

3) Sample Ranking and Calibration: We analyze the different sample ranking approaches and report the corresponding calibration performance on the M2CAI16-Workflow dataset. Expected Calibration Error (ECE) [61] is a common metric often used to measure calibration, and it is computed as the difference between the accuracy and predicted confidences calculated over several bins. We employ two calibration approaches in our work: temperature scaling (TS) [4] and label smoothing (LS) [20]. In P-CBLS, we calculate the confidence score to evaluate the difficulty of the sample based on the baseline model, which is trained using cross-entropy loss. In ls_P-CBLS, we use the model trained with the LS technique (ULS smoothing factor $\epsilon = 0.1$). In ts_P-CBLS, we use the standard model but with the TS technique (T = 2.63 for ResNet50, and T = 2.53 for DenseNet121). The results in Table V show that our P-CBLS, ts_P-CBLS, and ls_P-CBLS approaches attain lower calibration errors than the baseline.

4) Sample-Wise P-CBLS vs. pixel-Wise P-CBLS: The comparison between sample-wise P-CBLS and pixel-wise P-CBLS is shown in TABLE VI.

5) Hyper-Parameters of P-CBLS (ULS): We investigate the effect of different initial ULS smoothing factor ϵ , decay rate α , initial sample ratio λ , and epoch ratio for all samples E_{all} for ResNet50 on M2CAI16-Workflow Classification dataset (see

TABLE V

SAMPLE-WISE DIFFICULTY RANKING STUDY. TO OBTAIN THE SAMPLES BANK SORTED BY "EASINESS" FOR THE PACED LEARNING, WE UTILIZE

THREE DIFFERENT KINDS OF MODELS: (1) THE STANDARD (I.I.D.) TRAINING; (2) CALIBRATED MODEL WITH TEMPERATURE SCALE TECHNIQUE (T=2.63 FOR RESNET50, T=2.53 FOR DENSENET121); (3) THE CALIBRATED MODEL WITH CONSTANT LABEL SMOOTHING.

BASED ON THE THREE DIFFERENT SAMPLE BANKS, THE MODEL TRAINED WITH P-CBLS IS REFERRED TO AS P-CBLS, TS_P-CBLS,

LS_P-CBLS, RESPECTIVELY. WE REPORT THE CLASSIFICATION

PERFORMANCE AND CALIBRATION PERFORMANCE WITH THE ECE FOR TWO NETWORK ARCHITECTURES:

ResNet50 AND DENSENET121

I	Model	Accuracy	ECE↓
Baseline	ResNet50	68.16	0.2063
	P-CBLS	71.76	0.0955
Ours	ts_P-CBLS	71.80	0.1630
	ls_P-CBLS	70.67	0.0726
Baseline	DenseNet121	67.75	0.2070
	P-CBLS	70.43	0.1115
Ours	ts_P-CBLS	69.32	0.1957
	ls_P-CBLS	70.66	0.1735

TABLE VI

SEGMENTATION RESULTS FROM DIFFERENT TRAINING STRATEGIES BASED ON LINKNET34 [50] MODEL

	IoU	Dice
Linear CBLS	44.49	53.52
Exponential CBLS	47.35	54.95
sample wise P-CBLS	46.65	57.82
pixel wise P-CBLS	48.71	57.54

Fig. 8). The initial ULS smoothing factor ϵ of 0.5 generate the best accuracy, as shown in Fig. 8 (a). Therefore, we finetune the decay rate α with range $\alpha \in [0.8, 0.95]$ at a step of 0.05 with initial ULS smoothing factor ϵ of 0.5.

IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING

TABLE VII CLASSIFICATION RESULTS OF OUR CBLS AND OTHER BASELINES (CE, LS, ONLINE LS [53] AND DISTURB LABEL [62]) ON COMPUTER VISION DATASETS

-		CIFAR	CIFAR	Tiny
Model	Method	10	100	ImageNet
	CE	84.14	66.05	58.94
st5(LS [19]	84.70	66.69	59.90
ResNet50	Online LS [53]	82.08	66.20	59.89
Ses	Disturb Label [62]	81.22	66.17	58.84
Η	CBLS (Ours)	88.59	67.26	60.68
21	CE	78.11	68.09	63.53
et1	LS [19]	80.67	69.19	64.02
Ž	Online LS [53]	75.83	68.60	63.95
enseNet121	Disturb Label [62]	71.81	58.31	62.99
De	CBLS (Ours)	84.04	69.50	64.66

We did not see any further improvement from the finetuning operation. Next, we use the initial ULS smoothing factor ϵ of 0.5 and decay rate α of 0.9 for P-CBLS (ULS) experiments where we tune the initial sample ratio λ with range $\lambda \in [0.2, 0.6]$ at a step of 0.2 and the epoch ratio for all samples E_{all} with range $E_{all} \in [0.2, 0.6]$ at a step of 0.2. The initial sample ratio λ of 0.6 and epoch ratio for all samples E_{all} of 0.4 generate the best accuracy, as shown in Fig. 8 (b).

6) Validation on Computer Vision Datasets: In TABLE VII, we report the accuracy for three common computer vision datasets, including CIFAR10, CIFAR100, and Tiny-ImageNet. Compared to CE, LS [19], Online LS [53] and Disturb Label [62], our CBLS shows superior results.

VI. DISCUSSION AND CONCLUSION

Previous research has attempted to improve surgical recognition tasks by incorporating additional modules or making the technique computationally intensive. However, this has slowed prediction and limited its use in real-time robotic applications. The novel Paced-Curriculum By Label Smoothing (P-CBLS) method is proposed to improve the performance and generalization of deep neural networks (DNNs) without adding additional training parameters, which learns the samples from easy to complex with the gradually annealed smoothing factor. Extensive experiments on multiple robotic vision datasets for surgical recognition tasks demonstrate the effectiveness and robustness of our proposed CBLS and P-CBLS on different models. Our results and analyses suggest that curriculum learning can be developed by smoothing labels and controlling learning utility over the epochs. We also find that CBLS is better than P-CBLS for highly corrupted images with higher severity. As CBLS controls true probability during the training, it does not introduce additional parameters in the model. Therefore, CBLS and P-CBLS are model and task-agnostic curriculum learning strategies and are simple yet effective for many applications. Tuning the initial smoothing factor and decay rate in our CBLS approach may produce better predictions than our reported results using common hyper-parameters for both architectures. We investigate that after tuning, we can obtain 56.04 in CBLS and 55.94 in P-CBLS, which are higher than the reported results in TABLE I for the tool classification task. In future work, the confidence information can be integrated with label smoothing to re-weight the smoothing factor by class instance during CBLS training. It is also interesting to investigate the amalgamation of class distribution knowledge with the smoothing factor to design a curriculum scheme for the long-tailed dataset.

ACKNOWLEDGMENT

The authors would like to thank the support of Wang An for participating in the discussion of the project.

REFERENCES

- S. Rabanser, S. Günnemann, and Z. C. Lipton, "Failing loudly: An empirical study of methods for detecting dataset shift," 2018, *arXiv*:1810.11953.
- [2] D. C. Castro, I. Walker, and B. Glocker, "Causality matters in medical imaging," *Nature Commun.*, vol. 11, no. 1, pp. 1–10, Jul. 2020.
- [3] K. Stacke, G. Eilertsen, J. Unger, and C. Lundström, "Measuring domain shift for deep learning in histopathology," *IEEE J. Biomed. Health Informat.*, vol. 25, no. 2, pp. 325–336, Feb. 2021.
- [4] C. Guo, G. Pleiss, Y. Sun, and K. Q. Weinberger, "On calibration of modern neural networks," in *Proc. Int. Conf. Mach. Learn.*, 2017, pp. 1321–1330.
- [5] J. Mukhoti, V. Kulharia, A. Sanyal, S. Golodetz, P. H. S. Torr, and P. K. Dokania, "Calibrating deep neural networks using focal loss," 2020, arXiv:2002.09437.
- [6] Y. Bengio, J. Louradour, R. Collobert, and J. Weston, "Curriculum learning," in Proc. 26th Annu. Int. Conf. Mach. Learn., 2009, pp. 41–48.
- [7] M. P. Kumar, B. Packer, and D. Koller, "Self-paced learning for latent variable models," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 23, 2010, pp. 1189–1197.
- [8] C. Li, M. Zhang, and Y. He, "The stability-efficiency dilemma: Investigating sequence length warmup for training GPT models," 2021, *arXiv:2108.06084*.
- [9] Y. Wang, W. Gan, J. Yang, W. Wu, and J. Yan, "Dynamic curriculum learning for imbalanced data classification," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV)*, Oct. 2019, pp. 5017–5026.
- [10] S. Guo et al., "Curriculumnet: Weakly supervised learning from largescale web images," in *Proc. Eur. Conf. Comput. Vis. (ECCV)*, 2018, pp. 135–150.
- [11] H. Li and M. Gong, "Self-paced convolutional neural networks," in *Proc.* 26th Int. Joint Conf. Artif. Intell., Aug. 2017, pp. 2110–2116.
- [12] E. A. Platanios, O. Stretcu, G. Neubig, B. Poczos, and T. M. Mitchell, "Competence-based curriculum learning for neural machine translation," 2019, arXiv:1903.09848.
- [13] H. Zhao, X. Sun, J. Dong, Z. Dong, and Q. Li, "Knowledge distillation via instance-level sequence learning," 2021, arXiv:2106.10885.
- [14] G. Panagiotatos, N. Passalis, A. Iosifidis, M. Gabbouj, and A. Tefas, "Curriculum-based teacher ensemble for robust neural network distillation," in *Proc. 27th Eur. Signal Process. Conf. (EUSIPCO)*, Sep. 2019, pp. 1–5.
- [15] Q. Zhu, X. Chen, P. Wu, J. Liu, and D. Zhao, "Combining curriculum learning and knowledge distillation for dialogue generation," in *Findings of the Association for Computational Linguistics: EMNLP 2021.* Punta Cana, Dominican Republic: Association for Computational Linguistics, Nov. 2021, pp. 1284–1295. [Online]. Available: https://aclanthology.org/2021.findings-emnlp.111, doi: 10.18653/ v1/2021.findings-emnlp.111.
- [16] J. Wei et al., "Learn like a pathologist: Curriculum learning by annotator agreement for histopathology image classification," in *Proc. IEEE Winter Conf. Appl. Comput. Vis. (WACV)*, Jan. 2021, pp. 2473–2483.
- [17] X. Zhang, P. Shapiro, G. Kumar, P. McNamee, M. Carpuat, and K. Duh, "Curriculum learning for domain adaptation in neural machine translation," 2019, arXiv:1905.05816.
- [18] S. Sinha, A. Garg, and H. Larochelle, "Curriculum by smoothing," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 33, 2020, pp. 21653–21664.
- [19] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 2818–2826.

- [20] R. Müller, S. Kornblith, and G. Hinton, "When does label smoothing help?" 2019, arXiv:1906.02629.
- [21] M. Islam and B. Glocker, "Spatially varying label smoothing: Capturing uncertainty from expert annotations," in *Proc. Int. Conf. Inf. Process. Med. Imag.* Cham, Switzerland: Springer, 2021, pp. 677–688.
- [22] S. Basu and J. Christensen, "Teaching classification boundaries to humans," in *Proc. AAAI Conf. Artif. Intell.*, vol. 27, no. 1, 2013, pp. 109–115.
- [23] Y. Tang, Y.-B. Yang, and Y. Gao, "Self-paced dictionary learning for image classification," in *Proc. 20th ACM Int. Conf. Multimedia*, Oct. 2012, pp. 833–836.
- [24] D. R. Kepple, R. Engelken, and K. Rajan, "Curriculum learning as a tool to uncover learning principles in the brain," in *Proc. Int. Conf. Learn. Represent.*, 2021, pp. 1–11.
- [25] S. Roy, E. Krivosheev, Z. Zhong, N. Sebe, and E. Ricci, "Curriculum graph co-teaching for multi-target domain adaptation," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2021, pp. 5351–5360.
- [26] S. Basu, M. Gupta, P. Rana, P. Gupta, and C. Arora, "Surpassing the human accuracy: Detecting gallbladder cancer from USG images with curriculum learning," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2022, pp. 20886–20896.
- [27] B. Zoph, V. Vasudevan, J. Shlens, and Q. V. Le, "Learning transferable architectures for scalable image recognition," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 8697–8710.
- [28] E. Real, A. Aggarwal, Y. Huang, and Q. V. Le, "Regularized evolution for image classifier architecture search," in *Proc. AAAI Conf. Artif. Intell.*, vol. 33, 2019, pp. 4780–4789.
- [29] Y. Huang et al., "Efficient training of giant neural networks using pipeline parallelism," in *Proc. 33rd Conf. Neural Inf. Process. Syst.* (*NeurIPS*), Vancouver, BC, Canada, 2019, pp. 8–14.
- [30] M. Islam, L. Seenivasan, L. C. Ming, and H. Ren, "Learning and reasoning with the graph structure representation in robotic surgery," in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.* Cham, Switzerland: Springer, 2020, pp. 627–636.
- [31] M. Xu, M. Islam, C. Ming Lim, and H. Ren, "Learning domain adaptation with model calibration for surgical report generation in robotic surgery," 2021, arXiv:2103.17120.
- [32] A. Singh, A. Bay, B. Sengupta, and A. Mirabile, "On the dark side of calibration for modern neural networks," 2021, arXiv:2106.09385.
- [33] C. Szegedy et al., "Intriguing properties of neural networks," 2013, arXiv:1312.6199.
- [34] N. Carlini and D. Wagner, "Adversarial examples are not easily detected: Bypassing ten detection methods," in *Proc. 10th ACM Workshop Artif. Intell. Secur.*, Nov. 2017, pp. 3–14.
- [35] N. Carlini and D. Wagner, "Defensive distillation is not robust to adversarial examples," 2016, arXiv:1607.04311.
- [36] D. Hendrycks, M. Mazeika, and T. Dietterich, "Deep anomaly detection with outlier exposure," 2018, arXiv:1812.04606.
- [37] J. Steinhardt, P. W. Koh, and P. Liang, "Certified defenses for data poisoning attacks," in *Proc. 31st Int. Conf. Neural Inf. Process. Syst.*, 2017, pp. 3520–3532.
- [38] D. Hendrycks and T. Dietterich, "Benchmarking neural network robustness to common corruptions and perturbations," 2019, arXiv:1903.12261.
- [39] R. Geirhos, P. Rubisch, C. Michaelis, M. Bethge, F. A. Wichmann, and W. Brendel, "ImageNet-trained CNNs are biased towards texture; increasing shape bias improves accuracy and robustness," 2018, arXiv:1811.12231.
- [40] R. Zhang, "Making convolutional networks shift-invariant again," in Proc. Int. Conf. Mach. Learn., 2019, pp. 7324–7334.
- [41] A. P. Twinanda, S. Shehata, D. Mutter, J. Marescaux, M. De Mathelin, and N. Padoy, "EndoNet: A deep architecture for recognition tasks on laparoscopic videos," *IEEE Trans. Med. Imag.*, vol. 36, no. 1, pp. 86–97, 2016.
- [42] Y. Jin, Y. Long, C. Chen, Z. Zhao, Q. Dou, and P. Heng, "Temporal memory relation network for workflow recognition from surgical video," *IEEE Trans. Med. Imag.*, vol. 40, no. 7, pp. 1911–1923, Jul. 2021.
- [43] M. Allan et al., "2017 robotic instrument segmentation challenge," 2019, arXiv:1902.06426.
- [44] M. Allan et al., "2018 robotic scene segmentation challenge," 2020, arXiv:2001.11190.
- [45] C. González, L. Bravo-Sánchez, and P. Arbelaez, "ISINet: An instancebased approach for surgical instrument segmentation," in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.* Cham, Switzerland: Springer, 2020, pp. 595–605.

- [46] M. Xu, M. Islam, C. Ming Lim, and H. Ren, "Class-incremental domain adaptation with smoothing and calibration for surgical report generation," 2021, arXiv:2107.11091.
- [47] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.* (CVPR), Jun. 2016, pp. 770–778.
- [48] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 4700–4708.
- [49] S. Wang, Z. Xu, C. Yan, and J. Huang, "Graph convolutional nets for tool presence detection in surgical videos," in *Proc. Int. Conf. Inf. Process. Med. Imag.* Cham, Switzerland: Springer, 2019, pp. 467–478.
- [50] A. Chaurasia and E. Culurciello, "LinkNet: Exploiting encoder representations for efficient semantic segmentation," in *Proc. IEEE Vis. Commun. Image Process. (VCIP)*, Dec. 2017, pp. 1–4.
- [51] A. A. Shvets, A. Rakhlin, A. A. Kalinin, and V. I. Iglovikov, "Automatic instrument segmentation in robot-assisted surgery using deep learning," in *Proc. 17th IEEE Int. Conf. Mach. Learn. Appl. (ICMLA)*, Dec. 2018, pp. 624–628.
- [52] L.-C. Chen, Y. Zhu, G. Papandreou, F. Schroff, and H. Adam, "Encoder-decoder with atrous separable convolution for semantic image segmentation," in *Proc. Eur. Conf. Comput. Vis. (ECCV)*, 2018, pp. 801–818.
- [53] C.-B. Zhang et al., "Delving deep into label smoothing," 2020, arXiv:2011.12562.
- [54] Y. Wang, X. Ma, Z. Chen, Y. Luo, J. Yi, and J. Bailey, "Symmetric cross entropy for robust learning with noisy labels," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV)*, Oct. 2019, pp. 322–330.
- [55] M. Cornia, M. Stefanini, L. Baraldi, and R. Cucchiara, "Meshed-memory transformer for image captioning," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2020, pp. 10578–10587.
- [56] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, "BLEU: A method for automatic evaluation of machine translation," in *Proc. 40th Annu. Meeting Assoc. Comput. Linguistics*, 2001, pp. 311–318.
- [57] C.-Y. Lin, "ROUGE: A package for automatic evaluation of summaries," in *Text Summarization Branches Out*. Barcelona, Spain: Association for Computational Linguistics, Jul. 2004, pp. 74–81. [Online]. Available: https://aclanthology.org/W04-1013
- [58] A. Lavie and A. Agarwal, "Meteor: An automatic metric for MT evaluation with high levels of correlation with human judgments," in *Proc. 2nd Workshop Stat. Mach. Transl.*, 2007, pp. 65–72.
- [59] R. Vedantam, C. L. Zitnick, and D. Parikh, "CIDEr: Consensus-based image description evaluation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2015, pp. 4566–4575.
- [60] Y. Pan, T. Yao, Y. Li, and T. Mei, "X-linear attention networks for image captioning," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.* (CVPR), Jun. 2020, pp. 10971–10980.
- [61] M. P. Naeini, G. Cooper, and M. Hauskrecht, "Obtaining well calibrated probabilities using Bayesian binning," in *Proc. 29th AAAI Conf. Artif. Intell.*, 2015, pp. 1–7.
- [62] L. Xie, J. Wang, Z. Wei, M. Wang, and Q. Tian, "DisturbLabel: Regularizing CNN on the loss layer," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 4753–4762.



Mengya Xu received the B.Eng. degree in information engineering from Soochow University, Suzhou, China, in 2018, and the M.Sc. degree in electrical and computer engineering from the National University of Singapore, Singapore, where she is currently pursuing the Ph.D. degree with the Department of Biomedical Engineering. Her research interests include vision-language multimodality-based surgical scene understanding, supervised by Prof. Hongliang Ren.



Mobarakol Islam received the Ph.D. degree from the NUS Graduate School for Integrative Sciences and Engineering (NGS), National University of Singapore, in December 2019. He is currently a Post-Doctoral Fellow with the Department of Computing, Imperial College London, under Dr. Ben Glocker in BioMedIA Laboratory. His research interests include the interdisciplinary field of deep learning, medical image analysis, and robotic visual perception.



Hongliang Ren (Senior Member, IEEE) received the Ph.D. degree in electronic engineering (specialized in biomedical engineering) from The Chinese University of Hong Kong (CUHK) in 2008. He has been navigating his academic journey through The Chinese University of Hong Kong, UC Berkeley, Johns Hopkins University, Children's Hospital Boston, Harvard Medical School, Children's National Medical Center, USA, and the National University of Singapore. His research interests include biorobotics and intelligent systems,

medical mechatronics, continuum, and soft flexible robots and sensors, multisensory perception, learning and control in image-guided procedures, deployable motion generation, compliance modulation/sensing, cooperative and context-aware sensors/actuators in human environments, robotic surgery, flexible robotics, and machine artificial intelligence. He was a recipient of the IFMBE/IAMBE Early Career Award in 2018, the Interstellar Early Career Investigator Award in 2018, and the ICBHI Young Investigator Award in 2019. He also receives numerous international conference awards, including Best Conference Paper Awards at IEEE ROBIO 2019, IEEE RCAR 2016, IEEE CCECE 2015, IEEE Cyber 2014, and IEEE ROBIO 2013. He has served as an active Organizer and a Contributor on the committees for numerous robotics conferences, including a variety of roles in the flagship IEEE Conference on Robotics and Automation (ICRA), IEEE Conference on Intelligent Robots and Systems (IROS), and other domain conferences, such as ROBIO/BIOROB/ICIA. He has delivered numerous invited keynotes/talks at flagship conferences/workshops at ICRA/IROS/ROBIO/ICIA. He served as the Publicity Chair for ICRA 2017, concurrently as the Organizing Chair for ICRA 2017 workshop on Surgical Robots, and the video Chair for ICRA 2021. He serves as an Associate Editor for IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING and Medical and Biological Engineering and Computing (MBEC).



Ben Glocker received the Ph.D. degree from TU Munich. He is currently a Professor in machine learning for imaging with the Department of Computing, Imperial College London, where he coleads the Biomedical Image Analysis Group. He also leads the HeartFlow-Imperial Research Team and he is the Head of ML Research with Kheiron Medical Technologies. He was a Post-Doctoral Researcher with Microsoft and a Research Fellow with the University of Cambridge. His research interests include the intersection of medical imaging and artificial intelligence, aiming to build safe and ethical computational tools

for improving image-based detection and the diagnosis of disease.