Segmentation Consistency Training:
Out-of-Distribution Generalization for Medical
Image Segmentation

Birk Torpmann-Hagen
University of Oslo
birk.torpmann.hagen@gmail.com

Vajira Thambawita
SimulaMet
vajira@simula.no

Kyrre Glette
University of Oslo
kyrrehg@ifi.uio.no

Pål Halvorsen
SimulaMet
paalh@simula.no

Michael A. Riegler
SimulaMet
michael@simula.no

Abstract

Generalizability is seen as one of the major challenges in deep learning, in particu-
lar in the domain of medical imaging, where a change of hospital or in imaging
routines can lead to a complete failure of a model. To tackle this, we introduce Consis-
tency Training, a training procedure and alternative to data augmentation based
on maximizing models’ prediction consistency across augmented and unaugmented
data in order to facilitate better out-of-distribution generalization. To this end, we
develop a novel region-based segmentation loss function called Segmentation
Inconsistency Loss (SIL), which considers the differences between pairs of aug-
mented and unaugmented predictions and labels. We demonstrate that Consistency
Training outperforms conventional data augmentation on several out-of-distribution
datasets on polyp segmentation, a popular medical task.

1 Introduction

The last decade or so has seen a veritable revolution in artificial intelligence. This has in large part
been spearheaded by advancements in deep learning, the remarkable performance of which it can be
argued has rendered more conventional approaches practically obsolete. Recent work has, however,
highlighted that Deep Neural Networks (DNNs) are highly prone to exhibiting significant reductions
in performance when deployed in practical settings or otherwise Out of Distribution (OOD) data,
in spite of the fact that they readily exhibit high performance when evaluated on previously unseen
subsets of the training data [9, 11, 15, 18]. This is referred to as generalization failure.

Recent analyses attribute generalization failure to a structural misalignment between the features
that a given model learns through Empirical Risk Minimization (ERM) and the causal structure
which it ideally should encode [4, 11, 19, 26]. Generally, this misalignment occurs as a result of the
predictor - i.e., the trained model - learning spurious or otherwise causally unrepresentative features
that nonetheless perform well within the training distribution. This is often referred to as shortcut
learning [11] or the Clever Hans effect [21]. This behaviour is of course made evident as soon as the
predictor is exposed to any form of distributional shift which breaks these shortcuts, at which point it
will fail to generalize. These distributional shifts can range in magnitude, from common corruptions
such as noise or blurs [15] or spatial transforms [10], to practically imperceptible perturbations,
typically exemplified by adversarial attacks [6], or as will be shown in this work; simply collecting
data from different centers [29]. ERM does not and cannot guarantee invariance to these sorts

Preprint. Under review.
of distributional shifts, as it assumes that the distribution of the training data is Independent and Identically Distributed (IID) to the true distribution [13].

Closely related to shortcut learning is underspecification [9]. A machine learning pipeline can be considered underspecified when it can return any number of risk-equivalent predictors when evaluated on an IID holdout set, dependent only on the random variables used within the training procedure, i.e., dropout, weight initialization, and so on. Even with identical hyperparameters, a given training procedure can return any number of predictors, each having learned different patterns within the dataset. One predictor may have learned one shortcut, another may have learned a different shortcut, and the next may actually have learned features that correspond to the causal structure it is intended to learn. With ERM, and in particular with In-Distribution (InD)-oriented evaluation procedures, these are all erroneously considered equivalent.

EndoCV2021 provided an opportunity to investigate generalization failure and means by which to counteract them in the context of detection- and segmentation of colorectal polyps via a competition [3]. Though several teams made good progress towards increasing generalizability, the organizers’ review of the submissions [1] highlighted that every submitted model nevertheless exhibited significant performance reductions on the provided OOD datasets. Moreover, though a multitude of methods and approaches were tested, many of which did indeed benefit generalizability, few methods stood out as having the potential for significant further development.

To address these shortcomings, we introduce **Consistency Training**. We re-frame the problem of learning generalizable features into a matter of learning to not learn spurious features. This framework requires a *perturbation model*, which we in this work implement as simple data augmentation, and a differentiable quantity that represents the consistency of the predictions across perturbed and unperturbed inputs images, which we implement as *Segmentation Inconsistency Loss (SIL)*, a Jaccard-like loss function that quantifies the degree to which the segmentation probability maps exhibit unwarranted change after the input is perturbed. This loss function is then used in conjunction with a task-specific loss, in this work Jaccard loss. To increase the stability of the training routine, we also implement a dynamic weighting procedure for the two constituent components of the overall loss function. We show that Consistency Training increases generalization by a significant margin on all tested datasets when compared to conventional data augmentation. This framework is in other words a more performant alternative to data augmentation. Consistency Training leads to increased generalization with no additional overhead aside from the added computational cost involved with computing the auxiliary loss term and the memory required to store augmented and un-augmented versions of each batch. We summarize our contributions as following:

- We introduce SIL, a novel region-based segmentation loss function which quantifies the inconsistency between two predicted segmentations when the inputs are subjected to arbitrary augmentations.
- We propose a robust method of incorporating this loss function without a loss of segmentation performance through a dynamic weighting method.
- We demonstrate quantitatively that Consistency Training increases generalization when compared to data augmentation on three OOD datasets.

2 Related Work

**Generalization Failure.** The development of consistency training was in large part informed by recent advances in the understanding of generalization failure. D’Amour et al. [9] perform a thorough analysis of generalization failure through multiple case studies and highlight the role of underspecification therein. Geirhos et al. [11] explore the idea of shortcut learning in a similar manner, and highlight the importance of learning causally related features. Schölkopf [26] discusses the importance of causality in machine learning and how it relates to generalization failure.

**Generalizable Training Methods.** Increasing generalizability is an open problem, and there exists a large diversity of different approaches and perspectives on the matter in the literature. Arjovsky et al. [4] develop a novel training paradigm that makes use of multiple training environments in order to increase generalization. Robey et al. [23] employ a similar method and develop a model-based training paradigm which attempts to induce invariance to learned mappings between training environments. Sandfort et al. [25] also leverage generative networks, but instead simply use generated
CT-images as data augmentation, which they show improves OOD performance. Gokhale et al. \cite{12} compare the use of multiple data modification methods on robustness and generalization and find that data augmentation improves generalizability by a significant margin. Finally, Hendrycks et al. \cite{16} incorporate a consistency term into their loss function, in particular Jensen-Shannon distance between output probabilities - in order to facilitate robustness to distributional shifts for the image-classification task.

**Generalizable Polyp Segmentation.** In the context of polyp-segmentation, this work was motivated in large part by the findings in the proceedings of EndoCV2021 \cite{3}, which through the evaluation of submissions on multiple OOD datasets highlighted the significance of generalization failure. The winning submission to EndoCV2021, submitted by Thambawita et al. \cite{30}, leverages an ensemble-network in order to increase generalizability. Honga et al. \cite{17} also implement an ensemble-based model, which they show improves generalization. Gu et al. \cite{14} make use of domain composition and attention in an attempt to generalize to unseen domains.

In this regard, the existing works do not work well in the context of generalizability. Therefore, we introduced a novel training method with a new loss function to improve the generalizability of segmentation models on out-of-distribution datasets.

3 Approach

3.1 Consistency Training Method

This section will introduce Consistency Training, a training procedure wherein the objective is to optimize for invariance to a set of various image transformations by quantifying the degree to which the model outputs inconsistent predictions when its input is subjected to some transformations. This is achieved by giving the model two images: one which is augmented, and one which is not. These inputs are then passed through the model, resulting in two segmentation masks. The difference between these two predictions is then computed, and compared to the difference (if any) between the augmented and unaugmented segmentation labels. This is then incorporated into the loss-function such that the discrepancy between the expected prediction change and actual prediction change is minimized. This is illustrated in Figure 1. The next sections will cover the theoretical basis of this training procedure as well as the implementation of its constituent components.

![Figure 1: Diagram showing Consistency Training.](image)

Let \( Y := \{ y, \hat{y} := f(x) \} \) be the set consisting of the segmentation labels (masks) and predictions for the unperturbed samples, where \( f(\cdot) \) as before denotes the segmentation model. Let \( \epsilon(\cdot) \) be some perturbation function. Then, let \( A := \{ a := \epsilon(y), \hat{a} := f(\epsilon(x)) \} \) be the set consisting of masks and

3.2 Quantifying Segmentation Consistency

Let \( Y := \{ y, \hat{y} := f(x) \} \) be the set consisting of the segmentation labels (masks) and predictions for the unperturbed samples, where \( f(\cdot) \) as before denotes the segmentation model. Let \( \epsilon(\cdot) \) be some perturbation function. Then, let \( A := \{ a := \epsilon(y), \hat{a} := f(\epsilon(x)) \} \) be the set consisting of masks and
segmentation predictions when the input is subjected to a perturbation. **Segmentation Inconsistency** can then be quantified as:

\[
\mathcal{C}(y, a, \hat{y}, \hat{a}) = \frac{\sum\{y \oplus \hat{y} \ominus a \ominus \hat{a}\}}{\sum\{y \cup a \cup \hat{y} \cup \hat{a}\}}
\]  

(1)

\(\oplus\) here denotes the symmetric difference/disjunctive union. Equivalently, **Segmentation Consistency** can be expressed by:

\[
\mathcal{C}(y, a, \hat{y}, \hat{a}) = \frac{\sum\{y \cup \hat{y} \cup a \cup \hat{a}\} \ominus \{y \ominus \hat{y} \ominus a \ominus \hat{a}\}}{\sum\{y \cup a \cup \hat{y} \cup \hat{a}\}}
\]

(2)

These formulations are related by:

\[
\mathcal{C}(y, a, \hat{y}, \hat{a}) = 1 - \mathcal{C}(y, a, \hat{y}, \hat{a})
\]

In simple terms, this quantity corresponds to counting the number of pixels that change after the input is subjected to a perturbation, \(\hat{a} \ominus \hat{y}\), but discounting those we expect to change, \(a \ominus \hat{y}\). This is shown in Figure 2.

---

**Figure 2**: Visualisation of the operations used when computing segmentation-consistency and -inconsistency. Segmentation Inconsistency \(\mathcal{C}\) considers the ratio of pixel-predictions that underwent change as a result of a perturbation (here: augmentation), but should not have. Conversely, Segmentation Consistency \(\mathcal{C}\) considers the ratio of predictions that changed accordingly with respect to the perturbation.

Inconsistency as expressed in Equation (1) is not differentiable, and thus it cannot in its current state be used as a part of a loss function. Thus, a smooth extension of this metric is needed which can be achieved in much the same way as how the Jaccard loss can be derived from the Jaccard index - i.e., by using differentiable versions of the set functions.

We can extend the definition of the symmetric difference to \(\Theta(A, B) = A(1 - B) + B(1 - A)\). This, naturally, is equivalent to the standard symmetric difference if the values of A and B are binary. Similarly, the union operator can be extended as \(\bigcup(A, B) = A + B - AB\), and the intersection operator as \(\bigcap(A, B) = AB\). Like its binary equivalents, these operators maintain their associative and
commutative properties. One can optimize for consistency by replacing the operators in Equation (1) with these functions, which in turn can be used as a loss function:

\[ L_{sil}(y, \hat{y}, a, \hat{a}) = \sum \Theta(y, \hat{y}, a, \hat{a}) \bigcap (y, \hat{y}, a, \hat{a}) \] (3)

This loss function will from this point be referred to as SIL. Note that though this loss is implemented for binary segmentation in this task, it can be extended to multi-class segmentation by computing it for each channel and then reducing over channels.

### 3.3 Incorporating Consistency into Training

Using SIL as a loss function on its own is not really useful since it only expresses inconsistency, and is to a large extent agnostic to whatever object it is trying to segment. To illustrate, consider a model that predicts that every pixel is positive regardless of the content of the image, and that the augmentation strategy does not make use of augmentations that affect the labels. In this case, the consistency term will always be zero. For example, if the augmentation being performed is simply additive noise, the inconsistency term is equally well minimized if the model learns to predict that every pixel is positive as it would be if the model learned to be robust to additive noise. Consequently, it has to be combined with a segmentation loss, for instance Jaccard loss. A simple way to do this would be to simply add them together and normalize, i.e.:

\[ L(Y, A) = \frac{1}{2} \left[ L_{seg}(Y) + L_{sil}(Y, A) \right] \]

Preliminary experiments showed that this, however, exhibited some degree of instability during training. The model would readily get stuck in local minima where its predictions were indeed consistent, but also consistently predicting artifacts. Examples of this can be found in the Appendix.

To mitigate this, it is possible to employ a weighting strategy. Instead of simply adding the respective losses together, one may weight the individual components adaptively according to the InD segmentation performance, for instance mIoU. This way, the model will learn to predict generally correct segmentations early in the training, then start weighting consistency and as a result generalization more and more as the model sees improvements to its segmentation performance:

\[ L = (1 - IoU) \times L_{seg} + IoU \times L_{c} \] (4)

Using this formulation, the model will start off trying to learn features that contribute to generally improved segmentation performance, then as segmentation performance improves start principally focusing on learning to be consistent. If the model starts veering into areas in the loss-landscape that constitute poor segmentation performance, it will self-correct by weighing the segmentation loss more. In the implementation used in this study, the mIoU weights were calculated on a per-batch basis such that the model can quickly adapt if either of the respective objectives exhibit a degradation in performance during training.

### 4 Experiments and Results

To determine the generalizability of our methods, we trained ten instances each of four separate models using Consistency Training, as as well as with conventional data augmentation and no augmentation, which served as baselines. The generalizability of these models was then determined through computing mIoU on three OOD datasets. The mIoUs for models trained with Consistency training was then compared to the mIoUs of the two baselines across the three OOD datasets to ascertain the extent to which it impacts generalization.

#### 4.1 Experimental Setup

**Models.** To evaluate the impact of Consistency Training sufficiently, it was tested across a range of different models. These models include DeepLabV3+ [8], Feature Pyramid Network (FPN) [22], UNet [24], and Tri-Unet [30].

The models were implemented in pytorch using the segmentation-models-pytorch library [31], using the library’s default values. This includes initialization with Imagenet-pretrained weights. Ten instances of each model were trained across each configuration in order to perform statistical analysis.
Datasets. Evaluating the generalizability of a given predictor requires testing it on OOD data. Though this can to some extent be achieved by carefully designing stress-tests [9], a more straight-forward approach is to simply leverage existing OOD datasets. To this end, a number of polyp-segmentation datasets were selected. The names, sizes, resolutions and availabilities of these datasets is shown in Table 1. Sample images and masks from the datasets can be seen in Figure 3. Kvasir-SEG was selected as the training dataset, and partitioned into a 80/10/10 split as training/validation/test.

Table 1: Dataset Overview. The training dataset is marked using "*".

| Dataset            | Resolution | Size | Availability |
|--------------------|------------|------|--------------|
| Kvasir-SEG* [20]   | Variable   | 1000 | Public       |
| Etis-LaribDB [28]  | 1255x966   | 196  | Public       |
| CVC-ClinicDB [5]   | 388x288    | 612  | Public       |
| EndoCV2020 [2]     | Variable   | 127  | On Request   |

![Sample images from the datasets. Kvasir-SEG (left column) was used as the training data, the remaining datasets are test-sets.](image)

Metrics We used two metrics to evaluate generalizability. To evaluate raw performance, we used mIoU, which is defined as follows:

\[
IoU(y, \hat{y}) = \frac{\sum\{y = \hat{y}\}}{\sum\{y = 1\} \cup \{\hat{y} = 1\}}
\]

Measuring the mIoU scores across all the aforementioned datasets, naturally, provides an indication of the generalizability of the given predictor. Though it is of course impossible to account for all
distributional shifts that may occur in deployment, high degrees of generalization across multiple datasets should nevertheless indicate a sufficient level of generalization.

**Statistical tests** Two different tests were used to ascertain statistical significance. In cases where the mIoUs distribution was approximately normally distributed, for instance when comparing mIoU samples for a given pair of models on one dataset, an independent-sample t-test was used. When comparing across models, the Mann-Whitney U-test was chosen due to the multi-modality to the resulting distributions. All p-values can be found in the supplementary material.

**Implementation details.** All experiments were conducted using Nvidia Tesla-V100 GPUs. The experiments were implemented in Python 3.7.9 using PyTorch 1.8.0 and segmentation-models-pytorch [31]. The source code as well as all of the raw data is available at https://anonymous.4open.science/r/SegmentationConsistencyTraining-84EB

The augmentation method used both for the baseline and as part of Consistency Training was implemented using the albumentations library [7], and consisted of the following transformations: RandomRotate90, GaussNoise, ImageCompression, OpticalDistortion and ColorJitter. For the regular augmentation baseline, the augmentation probability was set to 0.5, in which case all of the aforementioned transformations were applied. All hyperparameters can be found in the supplementary material.

### 4.2 Out of Distribution Generalization

Table 2 shows the mean mIoUs for models trained with and without data augmentation, and models trained with Consistency Training. Comparing Consistency Training and conventional data augmentation for each model, statistical significance was achieved for all models except the TriUnet on the Etis-LaribDB dataset, for the FPN and Unet on the CVC-ClinicDB dataset, and for the Unet on the EndoCV2020 dataset after an independent-sample t-test. When comparing across all tested models, Consistency Training improves generalization by a statistically significant margin (p<0.01) on all OOD datasets over conventional augmentation after a Mann-Whitney U-test. A bar-plot comparing the improvement due to Consistency Training and conventional data augmentation is shown in Figure 4. This shows that Consistency Training can be considered a more generalizable alternative to data augmentation.

![Figure 4: Improvements due Consistency Training and Data Augmentation as a percentage the mean mIoU without augmentation across datasets.](image-url)
Table 2: Mean IoUs for training methods, precision truncated to 99% confidence. Consistency training entries with greater performance than conventional augmentation are highlighted in bold. If they are better by a statistically significant margin (p>0.99) after an independent sample two-sided t-test, they are also marked with a "*".

| Model         | No Augmentation | Vanilla Augmentation | Consistency Training |
|---------------|-----------------|----------------------|----------------------|
| Kvasir-SEG (In-Distribution) |                 |                      |                      |
| DeepLabV3+    | 0.822           | 0.850                | 0.852                |
| FPN           | 0.822           | 0.853                | 0.852                |
| TriUnet       | 0.817           | 0.841                | 0.845                |
| Unet          | 0.828           | 0.851                | 0.851                |
| Etis-LaribDB (Out of Distribution) |                 |                      |                      |
| DeepLabV3+    | 0.417           | 0.472                | 0.505*               |
| FPN           | 0.404           | 0.440                | 0.475*               |
| TriUnet       | 0.309           | 0.410                | 0.434                |
| Unet          | 0.403           | 0.447                | 0.481*               |
| CVC-ClinicDB (Out of Distribution) |                 |                      |                      |
| DeepLabV3+    | 0.684           | 0.733                | 0.740                |
| FPN           | 0.675           | 0.715                | 0.727*               |
| TriUnet       | 0.623           | 0.684                | 0.696                |
| Unet          | 0.679           | 0.717                | 0.730*               |
| EndoCV2020 (Out of Distribution) |                 |                      |                      |
| DeepLabV3+    | 0.608           | 0.676                | 0.676                |
| FPN           | 0.600           | 0.662                | 0.673                |
| TriUnet       | 0.577           | 0.667                | 0.684                |
| Unet          | 0.598           | 0.660                | 0.676*               |

5 Discussion and Conclusion

In this paper, we introduced Segmentation Consistency Training, a novel training procedure for segmentation which explicitly optimizes for consistent behaviour when an input subjected to augmentation. We showed that this improves OOD generalization by a statistically significant amount across several models when compared to conventional data augmentation. Moreover, we show that Consistency Training mitigates underspecification to a greater extent than data augmentation by analyzing performance variability.

5.1 Limitations

The batch size was kept constant across all experiments performed in this paper. However, as it can be argued that since Consistency Training implicitly increases the batch size, the experiments should ideally be repeated across a range of batch sizes.

Moreover, the experiments were only performed with one specific augmentation strategy. As it may be the case that the differences would be less significant if a more sophisticated strategy was used, repeating the experiment with a range of different augmentation functions and hyperparameter values is warranted.

As the experiments were only performed on polyp datasets, it can also be argued that it is uncertain whether Consistency Training has similar impacts on other segmentation tasks.

Finally, a larger number of samples should ideally have been collected across a wider diversity of model architectures. Increasing the granularity of the findings by other means, for instance by using a greater number of OOD datasets or designing parameterized stress-tests may also be warranted in order to develop a more thorough understanding of the impact of our methods.
5.2 Future Work

We plan to investigate a number of potential improvements of this framework. Consistency was for instance in this paper quantified as the symmetric difference between the expected change in the output due to augmentation and the actual change due to augmentation. This is largely agnostic to the augmentation being performed. However, it may be beneficial to take the nature of these augmentations into account. If the image is subjected to a 90 degree rotation, for instance, the prediction would following the notion of consistency as used in this work be considered perfectly consistent so long as the pixels corresponding to the polyps are rotated, and the incorrectly classified pixels remain unchanged. However, if the model instead learns to rotate all of the pixels - even those that are incorrectly classified - it may learn a more accurate representation of what constitutes consistent behavior under rotation. That means, instead of expressing inconsistency as in eq. (3), one can adjust the expected change term $a \oplus y$ to $\hat{y} \ominus \epsilon(\hat{y})$ such that also incorrect predictions can be considered consistent so long as they change in accordance to the nature of the perturbation model $\epsilon(\cdot)$. The resulting loss function can then be expressed as:

$$\mathcal{C}(\hat{y}, \hat{a}) = \sum_{\Theta(\hat{y}, \hat{a}, \hat{y}, \epsilon(\hat{y}))}$$

Which is equivalent to:

$$\mathcal{C}(\hat{y}, \hat{a}) = \sum_{\Theta(\hat{y}, \hat{a}, \epsilon(\hat{y}))}$$

This also has the advantage of being independent of the labels themselves. This may alleviate complications that may arise as a consequence of poor and/or incomplete labeling which would otherwise affect what the models learn to associate with consistent behaviour.

Repeating the experiments in this paper on a multitude of other segmentation tasks, for instance scene segmentation for autonomous vehicles, is also warranted. Evaluating Consistency Training through the use of stress-tests, for instance by augmenting datasets with a disjoint set of transformations as those used for training, may also provide some insights.

Further, one could investigate whether the consistency-training framework also can be implemented in the context of classification, object detection, or other applications of Deep Learning, and if similar improvements to generalizability can be shown in other domains.

Finally, one may compare the learned features of models trained with Consistency Training and the learned features of models trained conventionally. This could for instance be achieved through the use of Grad-CAM [27] or similar methods, and may be beneficial towards determining whether the model has learned at least partial invariance to the given augmentations.

6 Acknowledgment

The research presented in this paper has benefited from the Experimental Infrastructure for Exploration of Exascale Computing (eX3), which is financially supported by the Research Council of Norway under contract 270053.

References

[1] Sharib Ali et al. Assessing generalisability of deep learning-based polyp detection and segmentation methods through a computer vision challenge. 2022. DOI: 10.48550/ARXIV.2202.12031. URL: https://arxiv.org/abs/2202.12031.

[2] Sharib Ali et al., eds. EndoCV2020: 2nd International Workshop and Challenge on Computer Vision in Endoscopy. Vol. 2595. Iowa, USA: CEUR Workshop Proceedings, 2020. URL: http://ceur-ws.org/Vol-2595/.

[3] Sharib Ali et al., eds. Proceedings of the 3rd International Workshop and Challenge on Computer Vision in Endoscopy (EndoCV 2021) co-located with with the 17th IEEE International Symposium on Biomedical Imaging (ISBI 2021).

[4] Martin Arjovsky et al. Invariant Risk Minimization. 2019. DOI: 10.48550/ARXIV.1907.02893. URL: https://arxiv.org/abs/1907.02893.
Veit Sandfort et al. “Data augmentation using generative adversarial networks (CycleGAN) to improve generalizability in CT segmentation tasks”. In: Scientific Reports 9 (Nov. 2019). DOI: 10.1038/s41598-019-52737-x.

Bernhard Schölkopf. Causality for Machine Learning. 2019. DOI: 10.48550/ARXIV.1911.10500. URL: https://arxiv.org/abs/1911.10500.

Ramprasaath R. Selvaraju et al. “Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization”. In: International Journal of Computer Vision 128.2 (Oct. 2019), pp. 336–359. DOI: 10.1007/s11263-019-01228-7. URL: https://doi.org/10.1007/s11263-019-01228-7.

Juan Silva et al. “Toward embedded detection of polyps in wce images for early diagnosis of colorectal cancer”. In: International journal of computer assisted radiology and surgery 9.2 (2014), pp. 283–293. DOI: https://doi.org/10.1007/s11548-013-0926-3.

Vajira Thambawita et al. “An Extensive Study on Cross-Dataset Bias and Evaluation Metrics Interpretation for Machine Learning Applied to Gastrointestinal Tract Abnormality Classification”. In: ACM Trans. Comput. Healthcare 1.3 (June 2020). ISSN: 2691-1957. DOI: 10.1145/3386295. URL: https://doi.org/10.1145/3386295.

Vajira Thambawita et al. “DivergentNets: Medical Image Segmentation by Network Ensemble”. In: Proceedings of the 3rd International Workshop and Challenge on Computer Vision in Endoscopy (EndoCV 2021) co-located with with the 17th IEEE International Symposium on Biomedical Imaging (ISBI 2021). 2021, pp. 27–38. URL: https://arxiv.org/abs/2107.00283.

Pavel Yakubovskiy. Segmentation Models Pytorch. https://github.com/qubvel/segmentation_models.pytorch. 2020.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]. See fig. 4 and table 2.
   (b) Did you describe the limitations of your work? [Yes]. See section 5.1
   (c) Did you discuss any potential negative societal impacts of your work? [N/A]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]

2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A]
   (b) Did you include complete proofs of all theoretical results? [N/A]

3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes]. Code and data was made available in the form of a Github repository.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]. See supplementary material.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]. See fig. 4. If the improvement error bars are unsatisfactory, the raw data is also available on the github repository.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes]. This was discussed in Section 4.1 and in the acknowledgment.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]. See References list.
   (b) Did you mention the license of the assets? [N/A]
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes]. The code can be found on the github repository.
(d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [N/A]
(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [N/A]
Supplement to *Segmentation Consistency Training: Out-of-Distribution Generalization for Medical Image Segmentation*

Birk Torpmann-Hagen  
University of Oslo  
birk.torpmann.hagen@gmail.com

Vajira Thambawita  
SimulaMet  
vajira@simula.no

Kyrre Glette  
University of Oslo  
kyrrehg@ifi.uio.no

Pål Halvorsen  
SimulaMet  
paalh@simula.no

Michael A. Riegler  
SimulaMet  
michael@simula.no

1 Non-weighted Consistency Training

An effect of non-weighted consistency training is presented in Figure 1. The lack of weighting can sometimes induce instability; the model may learn to prioritize consistency at the cost of segmentation accuracy. In Figure 1, the model has learned to consistently predict positively along the margins of the image. As polyps are rarely found in these regions in the training data, the search will be biased toward predicting positively in these regions, as this will minimize the overall loss due to the reduced contribution from the consistency term. It should be noted, however, that these artifacts will gradually disappear given sufficient training. Nevertheless, the weighting scheme permits more efficient and stable training.

![Figure 1](image1.png)  
Figure 1: When the Inconsistency term is not modulated dynamically, the model can quickly learn to predict artifacts around the edges of the image. As polyps can rarely be found in these regions, the consistency term is minimized by predicting consistently wrong predictions where there typically are not polyps. To avoid instability in this regard, dynamic weighing is necessary.

Preprint. Under review.
2 Statistical Tests

Two different tests were used to ascertain statistical significance. In cases where the Mean Intersection over Unions (mIoUs) distribution was approximately normally distributed, for instance when comparing mIoU samples for a given pair of models on one dataset, an independent-sample t-test was used. When comparing across models, the Mann-Whitney U-test was chosen due to the multi-modality to the resulting distributions.

| Dataset       | U-Statistic | p-Value |
|---------------|-------------|---------|
| Kvasir-SEG    | 725.0       | 0.23673 |
| Etis-LaribDB  | 388.0       | 0.00004 |
| CVC-ClinicDB  | 491.0       | 0.00150 |
| EndoCV2020    | 411.0       | 0.00009 |

Table 1: Results from a Mann-Whitney U-test for each dataset when comparing the mIoUs for Consistency Training vs conventional data augmentation across models.

| Model         | CVC-ClinicDB | EndoCV2020 | Etis-LaribDB | Kvasir-SEG |
|---------------|--------------|------------|--------------|------------|
| DeepLabV3+    | 0.029        | 0.901      | **0.003**    | 0.444      |
| FPN           | **0.004**    | 0.038      | **0.005**    | 0.939      |
| TriUnet       | 0.211        | 0.024      | 0.141        | 0.330      |
| Unet          | **0.000**    | **0.001**  | **0.006**    | 0.899      |

Table 2: p-values for each model and dataset between the mIoUs of the given models trained with consistency training versus when trained with data augmentation.

3 Hyperparameters

Table 3: Overview of augmentation functions and corresponding non-default hyperparameters used in this work.

| Invariance             | Albumentation Function                                      |
|------------------------|-----------------------------------------------------------|
| Perspective            | Flip()                                                     |
|                        | RandomRotate90()                                          |
| Image quality          | GaussNoise(max=0.01)                                      |
|                        | ImageCompression(max=100, min=10)                         |
| Camera models          | OpticalDistortion(distort_limit=10)                       |
| Lighting conditions    | ColorJitter(brightness=0.2, hue=0.2, contrast=0.2, saturation=0.2) |
Table 4: Hyperparameters and objects used to train all models.

| Component   | Type                        | Hyperparameters                      |
|-------------|-----------------------------|---------------------------------------|
| Dataloader  | -                           | batch\_size = 8                       |
|             |                             | train/val/test split = 80/10/10       |
| Optimizer   | Adam                        | \( lr = 0.00001 \)                    |
| Scheduler   | Cosine Annealing w/ Warm Restarts | \( T_0 = 50 \)                       |
|             |                             | \( T_{mult} = 2 \)                    |
| Evaluation  | Loss-based Early Stopping   | \( epochs = 300 \)                    |