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Unravelling the effect of data augmentation transformations in polyp segmentation

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Introduction

* Deep learning for medical imaging analysis

Challenges [1-3]

- Relevance (clinical vs tech. interest)
- Acceptance (black box)
- Privacy and legal issues
- Lack of large annotated datasets
- Class imbalance
- Effective negative set
- Weak annotations

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Introduction

- Data augmentation [1-4]
  - Manipulate image appearance, quality, or layout
  - Reduce overfitting
  - Preserve label/mask

Which is the best data augmentation strategy for a particular problem?

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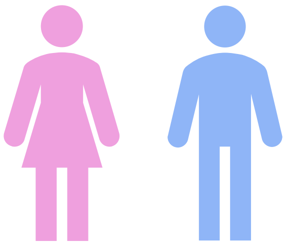
* Colorectal cancer [1,2]

Type	Incidence	Mortality
Breast	2.088.849	626.679
Colorectum	826.303	396.568
Cervix uteri	725.352	576.060



Type	Incidence	Mortality
Lung	1.368.524	1.184.947
Prostate	1.276.106	358.989
Colorectum	1.026.215	484.224

* Computer-aided detection (CADe) and diagnosis (CADx) in colonoscopy [3]:
  * Adequacy of inspection technique
  * Polyp identification
  * Optical biopsy

1, Cancer Today. https://bit.ly/2XjNgbo
2, Cancer Today. https://bit.ly/3gajQVM
3. Byrne, M.F.; Shahidi, N.; Rex, D.K. Will Computer-Aided Detection and Diagnosis Revolutionize Colonoscopy? Gastroenterology 2017, 153, 1460-1464.e1.

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* Publicly available datasets for polyp segmentation:

	Database	# Images	Ground truth
Medical images	CVC-EndoSceneStill	912	Binary mask (border, polyp, lumen and specular lights)
	Kvasir-SEG	1000	Binary mask (polyp)
	CVC-VideoClinicDB	36 videos (>30,000 frames)	Binary mask with elliptical approximation
Natural images	ImageNet	>14,000,000	Label and bounding box
	MSCoco	330,000	Binary mask, bounding box, person keypoints, captions
	PascalVOC	>19,000 images (>40,000 instances)	Binary mask and bounding box

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Work	Year	Rotation	Width Shift	Height shift	Shear	Zoom	Flip	Contrast	Brightness
Jha [1]	2020	--	-	-	-	✓	✓	-	✓
Guo [2]	2019	✓	-	-	-	✓	✓	-	✓
Kang [3]	2019	(-45°, 45°)	-	-	(-16°, 16°)	(0.5, 1.5)	✓	(0.5, 1.5)	(0.8, 1.5)
Akbari [4]	2018	10° interval, between 0°-290°	-	-	-	-	✓	-	-
Brandao [5]	2018	-	-	-	-	-	✓	-	-
Wichakam [6]	2018	up to 180°	(0, 20%)	(0, 20%)	up to 20%	(-0.8, 1.2)	✓	-	-
Wickstrom [7]	2018	(-90°, 90°)	-	-	(0, 0.4)	(0.8, 1.2)	-	-	-
Bardhi [8]	2017	✓	✓	✓	✓	-	✓	-	-
Li [9]	2017	✓	✓	✓	-	-	-	✓	-
Vázquez [10]	2017	(0°, 180°)	-	-	(0, 0.4)	(0.9, 1.1)	-	-	-

References are provided at the end of the presentation

Objective

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* HYPOTHESIS:

  The application of different transformations as well as different ranges for the same transformation might lead to differences in performance

* OBJECTIVE:

  To elucidate the effect of different image transformations and their ranges used for data augmentation for polyp segmentation

Material and Methods

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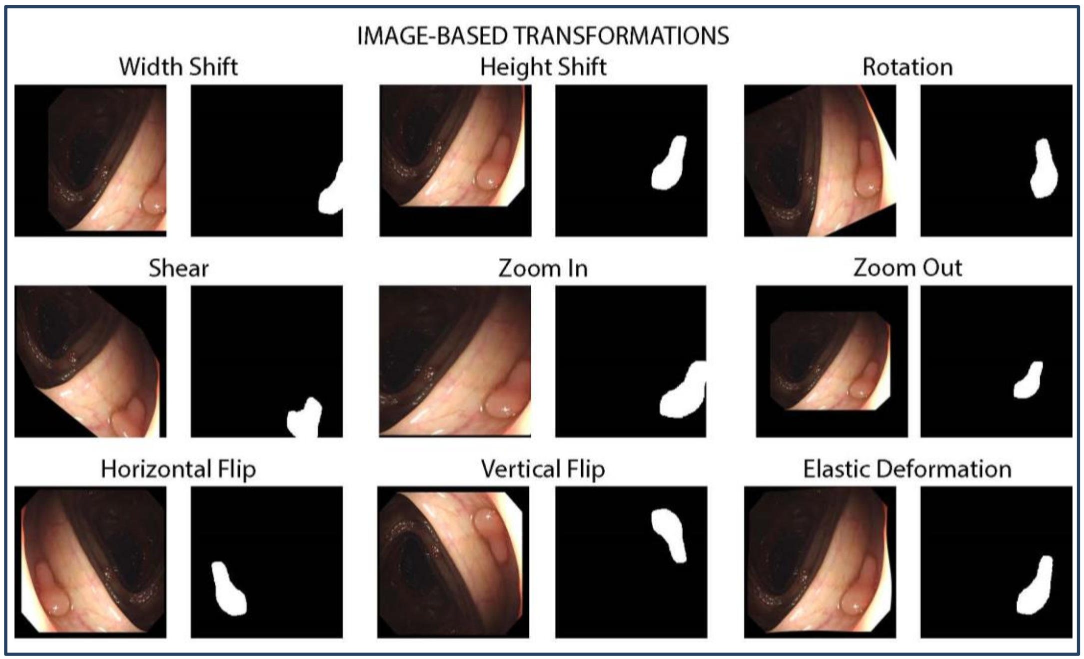
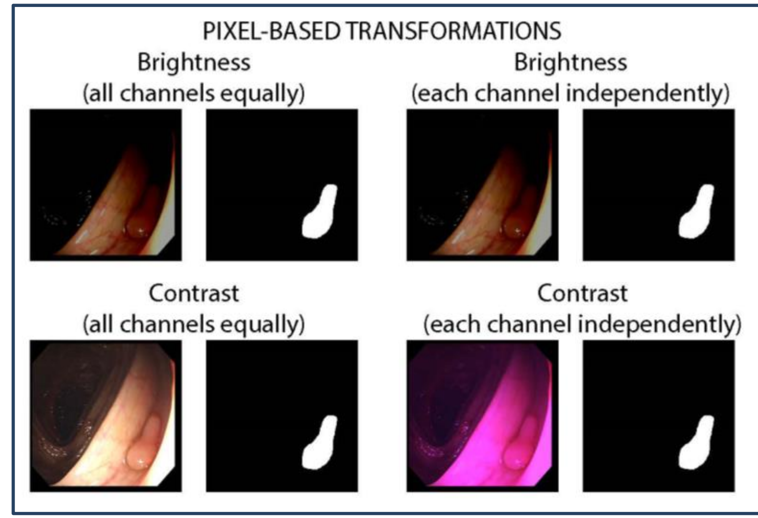
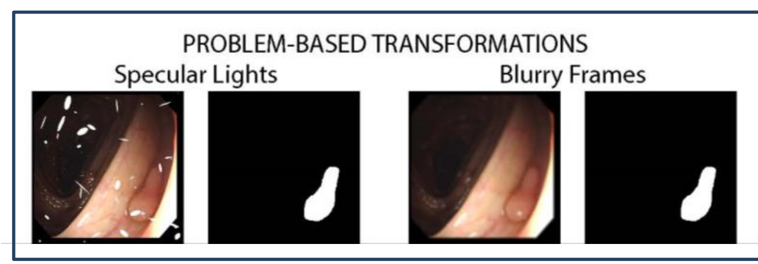
ORIGINAL IMAGE

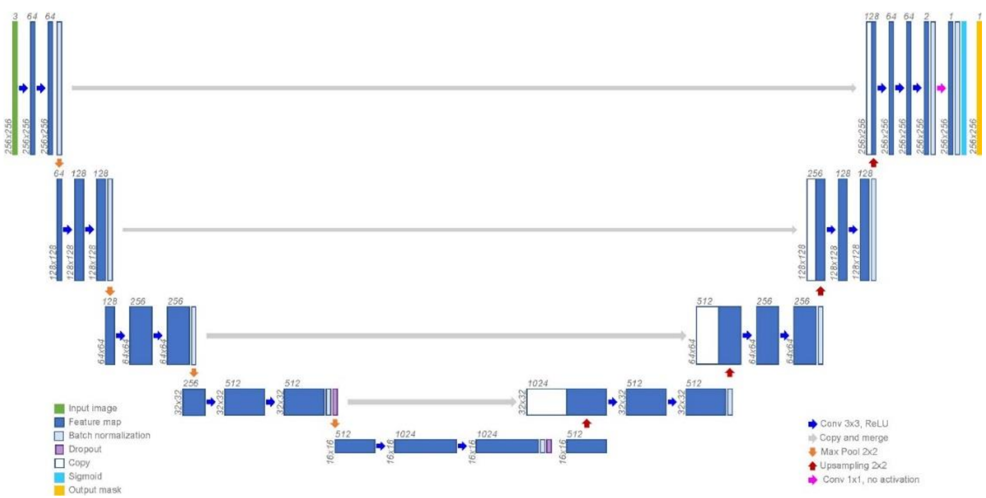






Material and Methods

- Architecture: U-Net based
  - pre-trained using CVC-VideoClinicDB
- Loss: $Loss = -\frac{1}{n}\sum_{i,j}\left(y_{i,j}\log\hat{y}_{i,j} + (1-\hat{y}_{i,j})\right)\log\left(1-\hat{y}_{i,j}\right) - \log J$
- Metric: $J = IoU(A,B) = \frac{|A\cap B|}{|A\cup B|} = \frac{|A\cap B|}{|A|+|B|-|A\cap B|}$



- Fixed training parameters
- Baseline: no data augmentation
- Each experiment is repeated 10 times
- 15 epochs
- Data augmentation on the flow
- Dataset: CVC-EndoSceneStill
  - Training set: 547
  - Validation set: 183
  - Test set: 182
- Statistical analysis
  - Kolmogorov-Smirnov
  - Wilcoxon-signed rank test

Results

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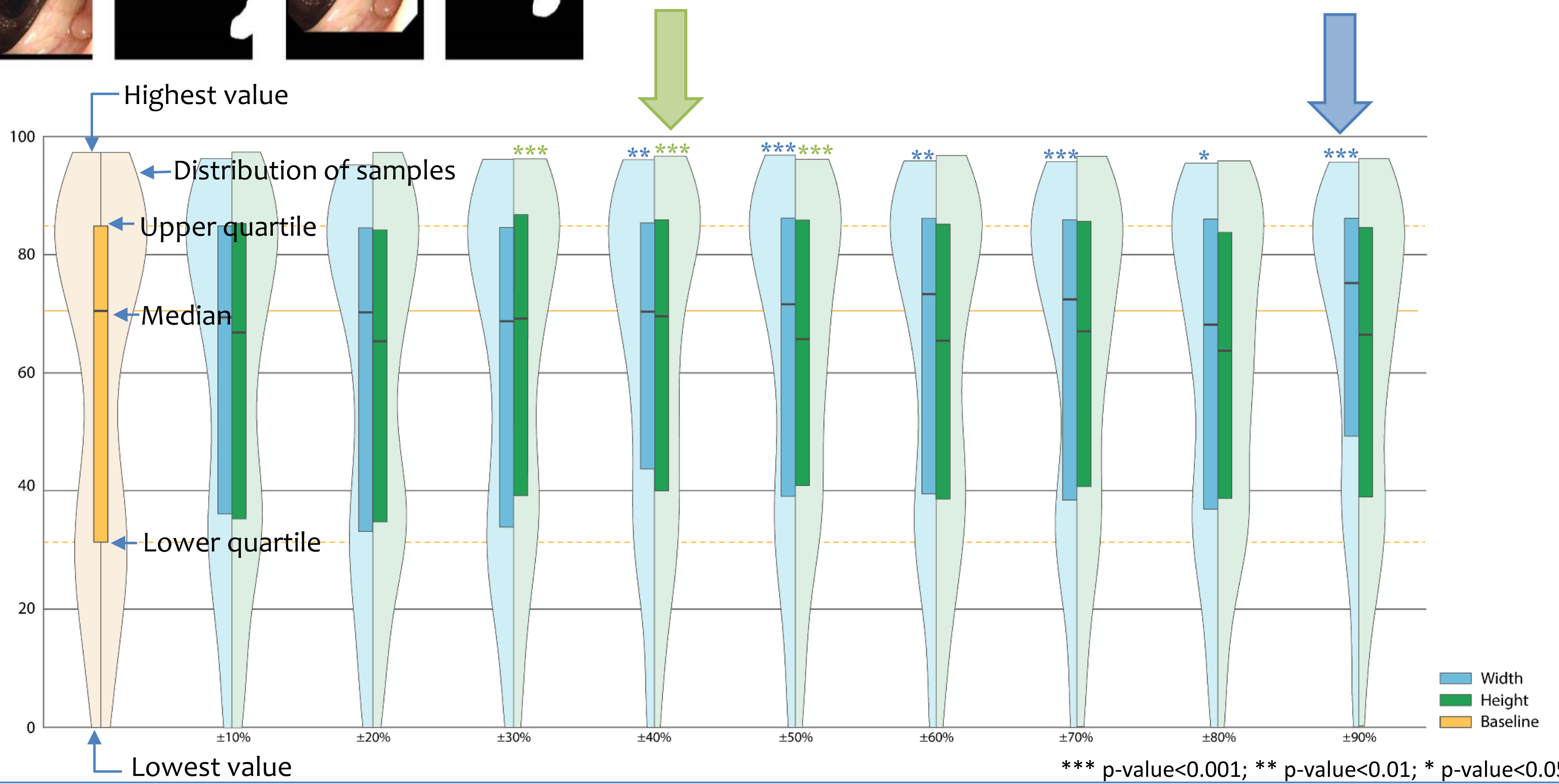
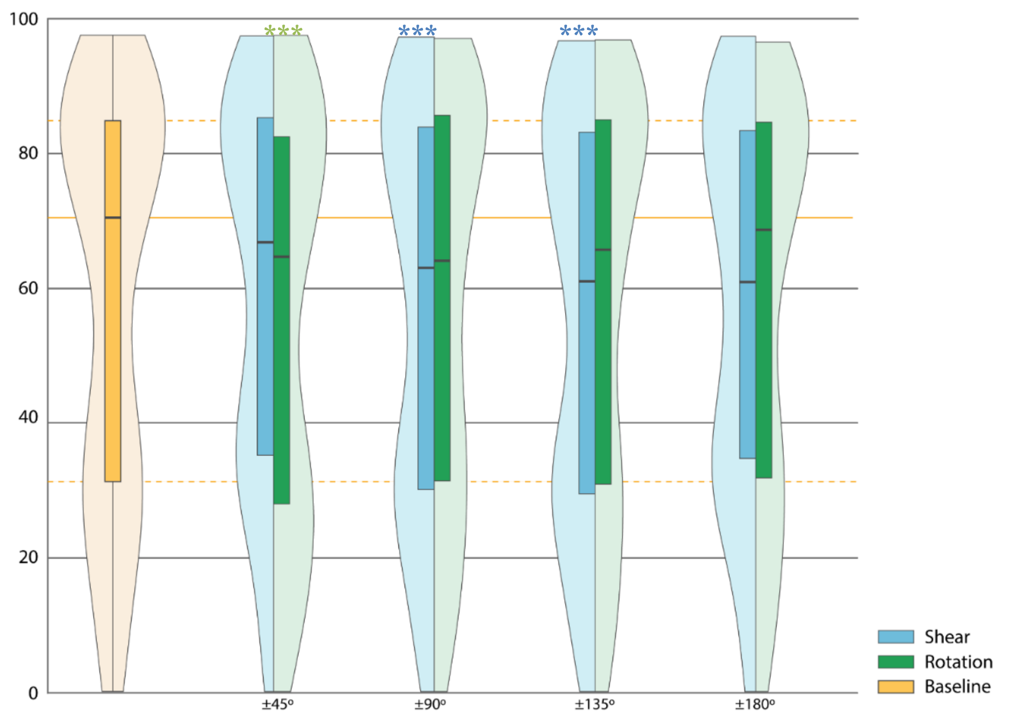
Width Shift Height Shift

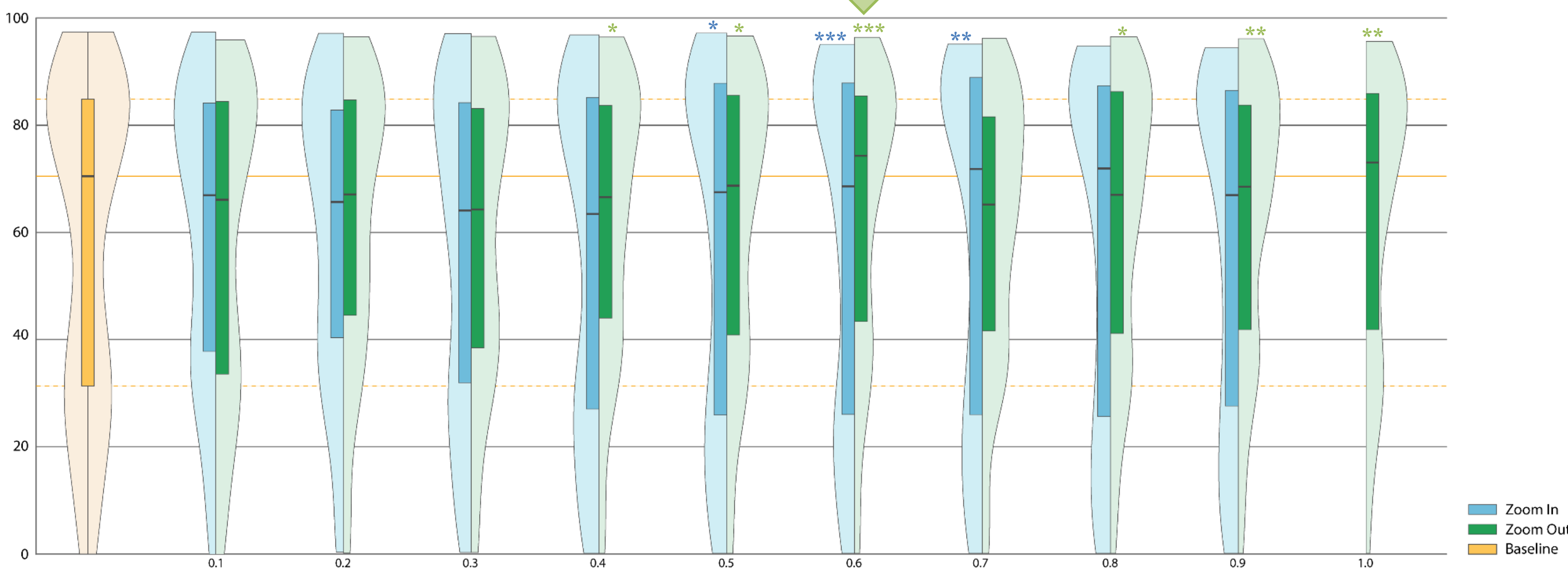


Results



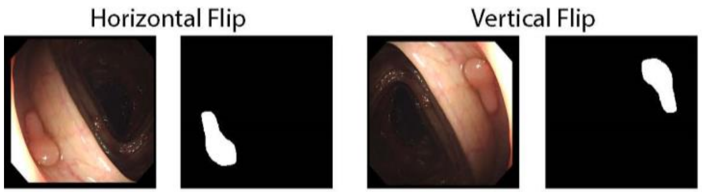
*** p-value<0.001; ** p-value<0.01; * p-value<0.05

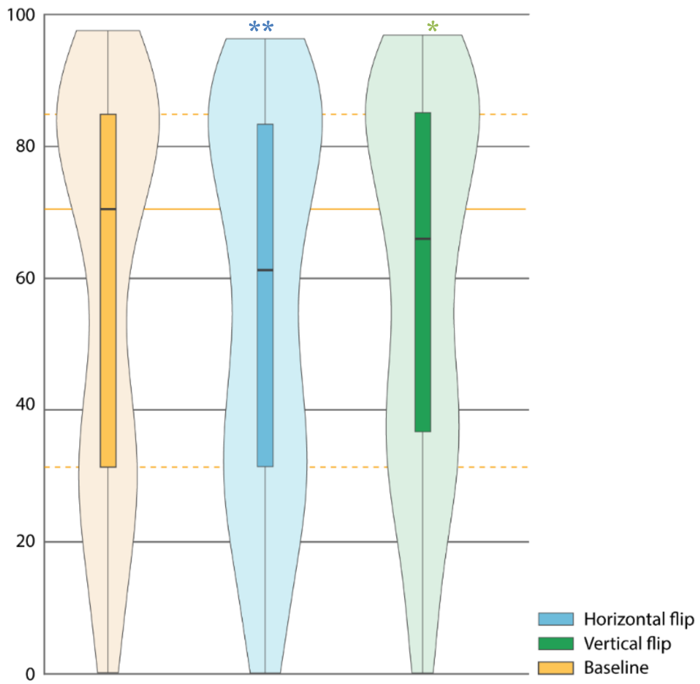
Results



*** p-value<0.001; ** p-value<0.01; * p-value<0.05

Results

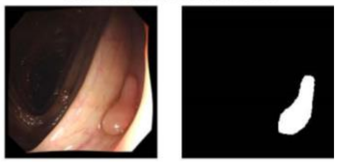


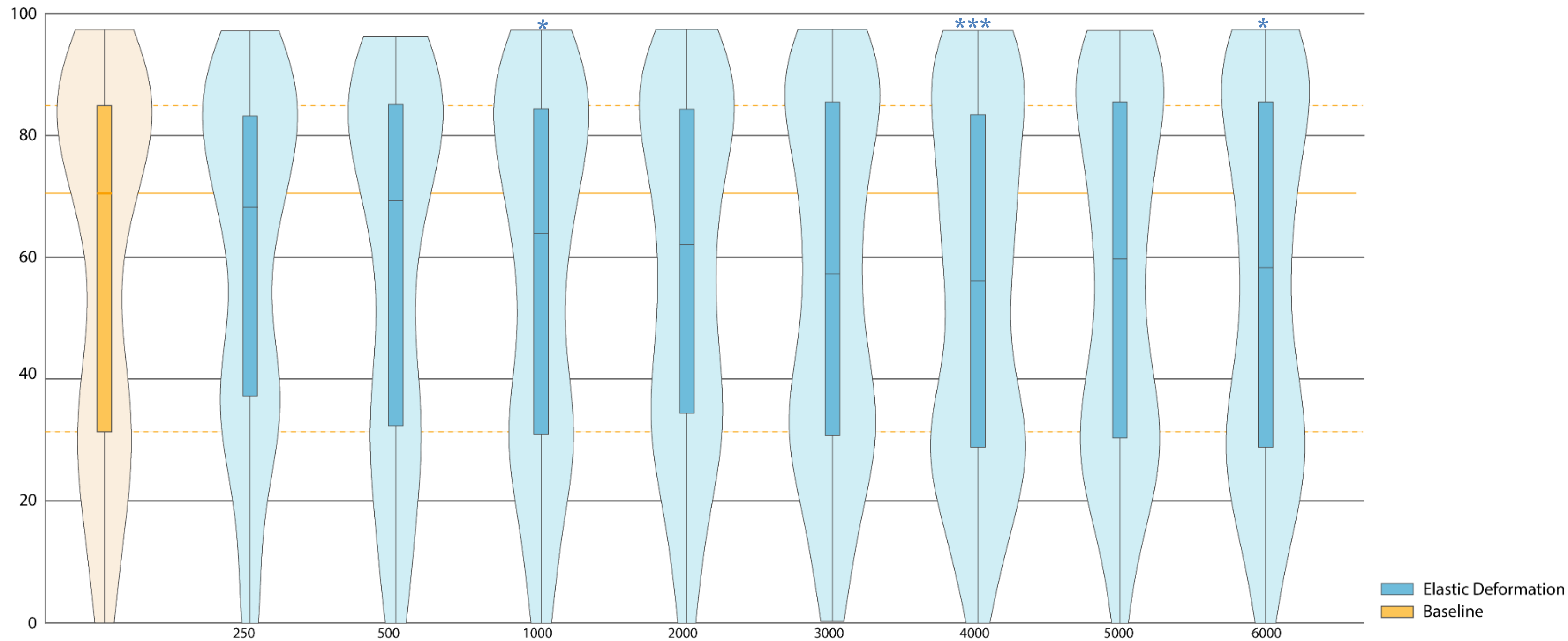


*** p-value<0.001; ** p-value<0.01; * p-value<0.05

Results

Elastic Deformation



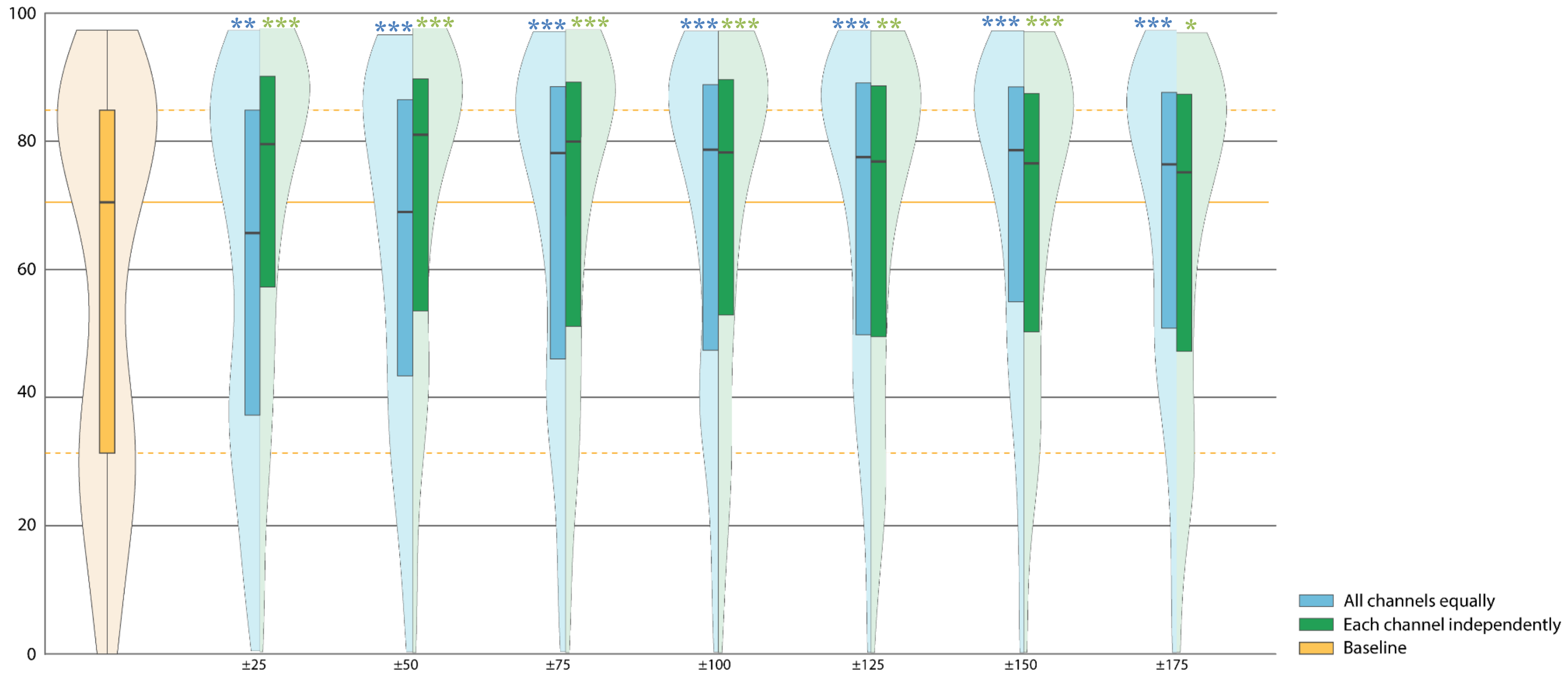


*** p-value<0.001; ** p-value<0.01; * p-value<0.05

Results

Brightness
(all channels equally)

Brightness
(each channel independently)



*** p-value<0.001; ** p-value<0.01; * p-value<0.05

Results

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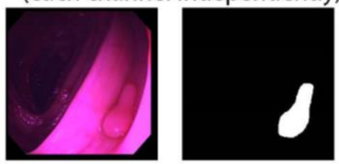
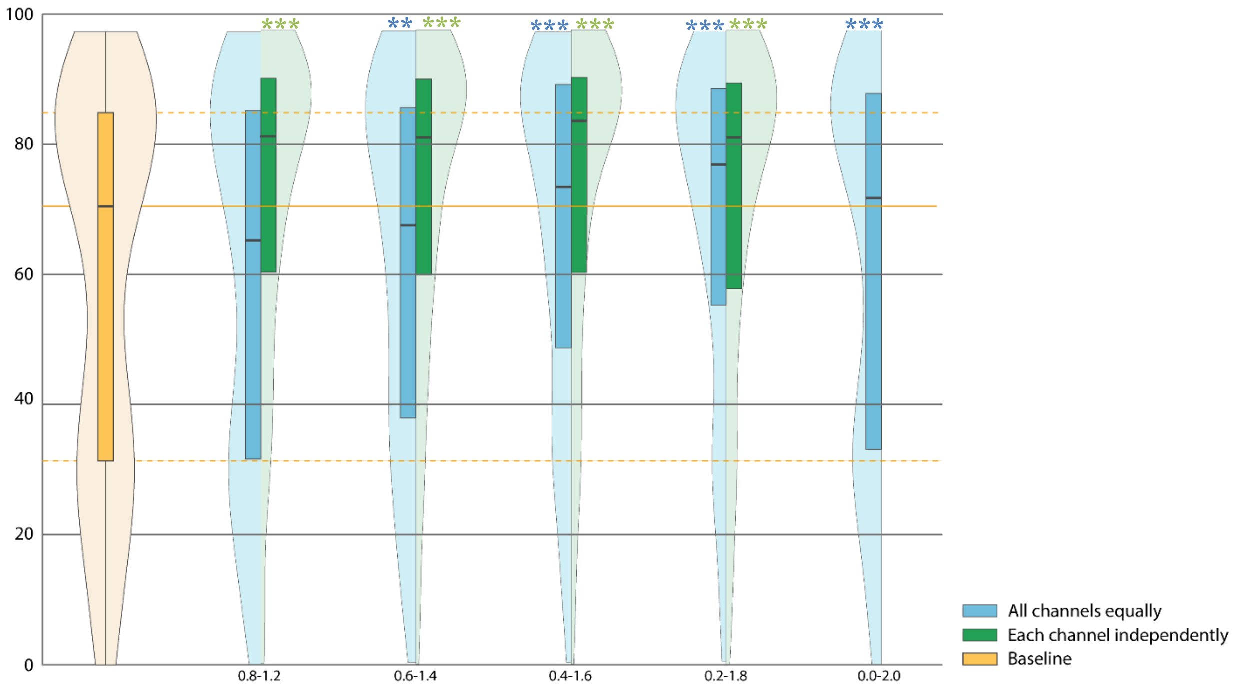
Contrast
(all channels equally)

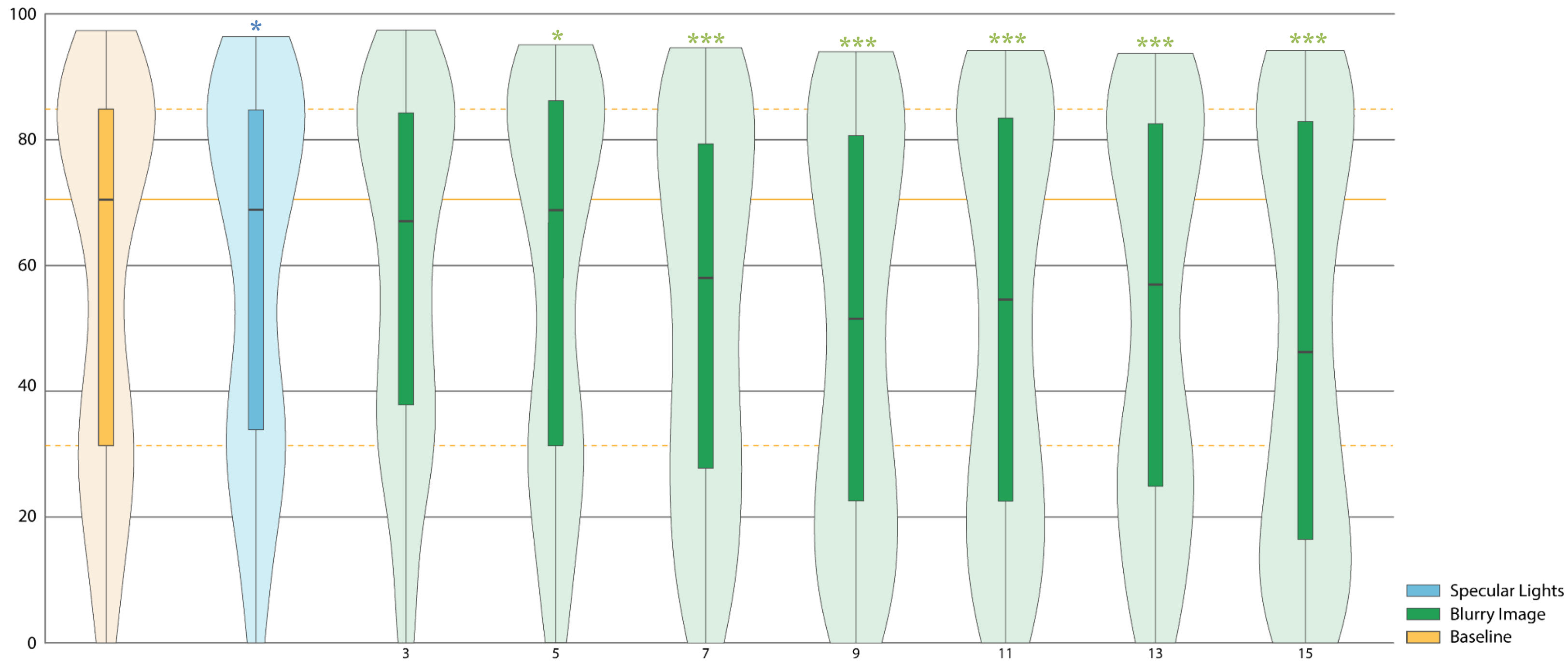
Contrast
(each channel independently)





*** p-value<0.001; ** p-value<0.01; * p-value<0.05

Results



*** p-value<0.001; ** p-value<0.01; * p-value<0.05

Results

* Best improvements:
  * Width: ± 40%
  * Height: ± 90%
  * Zoom in: 0.6
  * Brightness: ±25, each channel independently
  * Contrast: 0.4-1.6, each channel independently
  * Inclusion of specular lights

Conclusions

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* Three groups of transformations can be established:
  * Transformations that always improve the performance:
    * vertical flip
    * changes on brightness
    * changes on contrast
    * inclusion of specular lights
  * Transformations that always hinder the performance:
    * rotation
    * shear
    * horizontal flip
    * elastic deformation
    * blurry frames (mean filter)
  * Transformations whose effect on performance depends on the selected range:
    * height shift
    * width shift
    * zoom in
    * zoom out

Conclusions

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* Different transformations and ranges lead to differences in model performance.
* Pixel-based transformations show a great potential to improve polyp segmentation.
* Image-based transformations and their ranges should be carefully selected to not hinder the model performance and obtain the expected benefits of data augmentation.

Future works

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* Study different combinations of transformations
* Analyse the effect of these transformations in a different dataset (Kvasir-SEG)

References

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Thank you for your attention

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