SITB2021 - Poster Session

ViNotion

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

AnonImMed: An Open-Source Tool for Fast Anonymization of Medical Images

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Motivation

- Deep Learning requires training data in the form of images
- Medical images often contain privacy-sensitive text overlays
- Medical privacy-sensitive data is generally not allowed to be shared with (and stored by) researchers
- Anonymization of data, by removing all text, can solve this problem

Goals of this study

- **Automatically remove text overlays on medical image data**
- **Must achieve very high recall to preserve privacy**
  - **High precision is nice-to-have, but less important**
- **Fast processing speed on a portable device**

Network training

- Starting point: ICDAR pretrained EAST text detector
- Fine-tune to improve performance
  - Using data augmentation and synthetic text overlays

Training data

- ICDAR dataset, KvasirV2 dataset, private endoscopic images
- Data augmentation and synthetic text tailored to application

- Random synthetic text with application-specific properties
  - Random sans-serif font out of 2594 Google Fonts
  - Random font size and string length
  - Random symbols (ASCII letters, digits, punctuation)
  - Random color, biased towards white/light grey
- Data augmentation
  - Blurring by scaling, using random up-/downsampling methods
  - Applying random JPEG compression
  - Adding black/grey borders or performing full-image blocking
  - Adding Gaussian noise

Figure 1: ICDAR Data augmentation and synthetic text generation example.
Colored boxes show ground truth text positions.
Red boxes indicate synthetic data, blue boxes ICDAR ground truth.

Results

- Tests on unseen challenging small set of endoscopic images
- Finetuning with synthetic text improves performance over alternatives

Table 1: Scores on a manually selected challenging subset of endoscopic images.

Method	Seen medical images?	Precision	Recall
CharNet (pretrained)	×	0.99	0.68
EAST (pretrained, OpenCV)	×	0.96	0.64
EAST (pretrained, PyTorch)	×	0.99	0.80
EAST (augmented) ours	×	0.95	0.88
EAST (augmented+finetuned) ours	✓	0.98	**0.94**

Increasing execution speed

- Employing existing methods improves processing speed by factor 5
- Newly proposed "Mask mode" improves speed by another factor 2
  - Masks image with activation map instead of blacking out bboxes

Table 2: Impact of speed improvements on processing speed.
Measured on an RTX 2080 Ti at 1920x1080 px.

Engine	FP acc.	EAST opt.	DALI	JPEG Turbo	Mask Mode	Multi-core	Batch	msec	FPS
PyTorch	Fp32						1	263	3.8
PyTorch	Fp32	✓					1	189	5.3
PyTorch	Fp16	✓					1	152	6.6
TRT	Fp16	✓					1	127	7.9
TRT	Fp16	✓	✓				1	74.6	13.4
TRT	Fp16	✓	✓	✓			1	52.6	19.0
TRT	Fp16	✓	✓	✓			4	52.6	17.6
TRT	Fp16	✓	✓	✓	✓		1	48.1	20.8
TRT	Fp16	✓	✓	✓	✓		4	47.8	20.9
TRT	Fp16	✓	✓	✓	✓	✓	4	**29.3**	**34.1**

Conclusions

- **We designed a text-overlay anonymization tool for medical images**
- **Processing speed improved by a factor of 9x**
  - **Network itself is often not the bottleneck in a system**
- **Code available soon: github.com/SanderKlomp/AnonImMed**

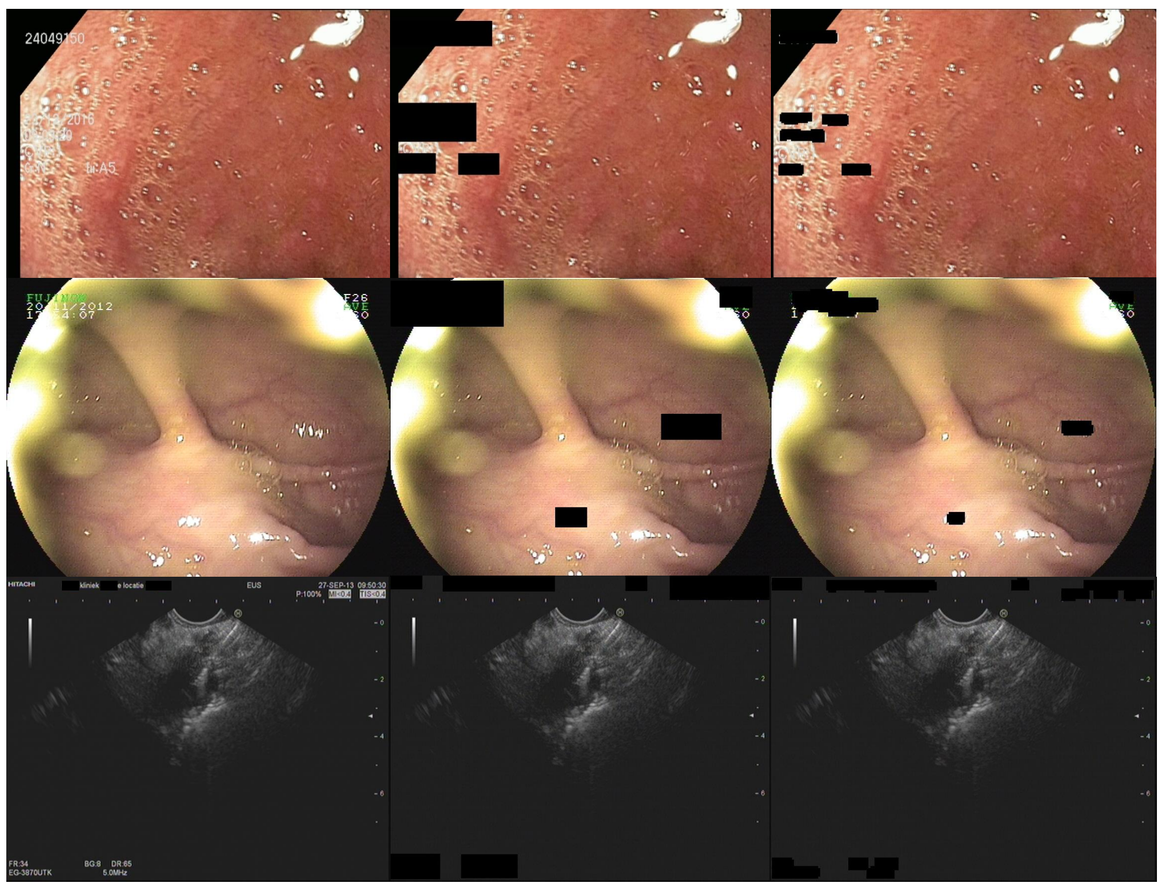

Figure 2: Examples of medical images (left) anonymized by blacking out detected bounding boxes (middle) and using faster mask-based blackout (right).
Middle row shows a challenging example with 2 false positive detections on reflections.