Paired Image to Image Translation for Strikethrough Removal from Handwritten Words

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Strikethrough Removal

removing strikethrough strokes, returning the original, clean words

Primary use case:

research questions for which struck-through (deleted) words are of interest, e.g. **genetic criticism**

→ pre-processing for humans and machines

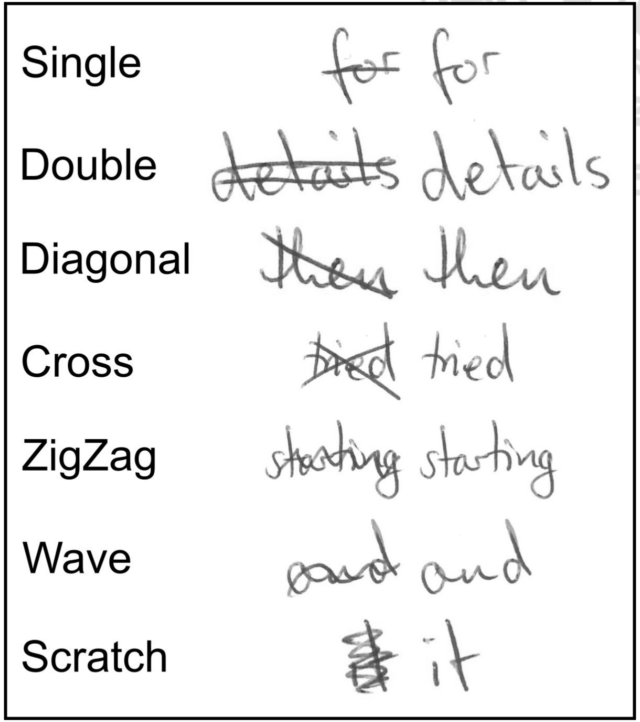


Fig.: Examples of different types of struck-through words and respective clean ground truth.

General Approach

- paired image to image translation
  - from source domain (struck words) to target domain (clean words)
- segmentation-based, i.e. focus on struck-through words

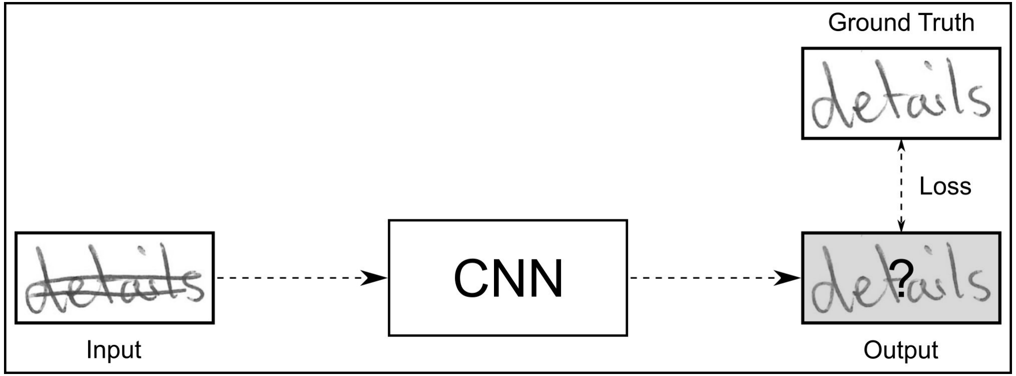


Fig.: Schematic view of paired image to image translation for strikethrough removal.

Examined Models

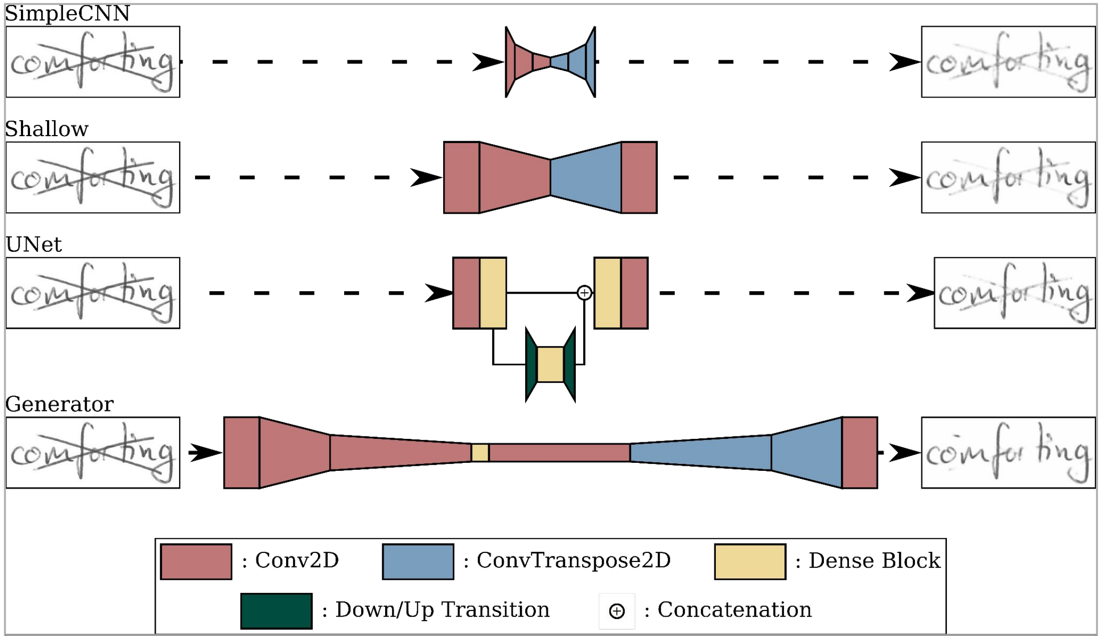


Fig.: Schematic overview over the four architectures, examined in a paired setting.

+ Attribute-Guided CycleGAN from [1]

→ unpaired approach

[1] Heil, R., Vats, E., Hast, A. (2021). Strikethrough Removal from Handwritten Words Using CycleGANs. ICDAR 2021

Examined Models

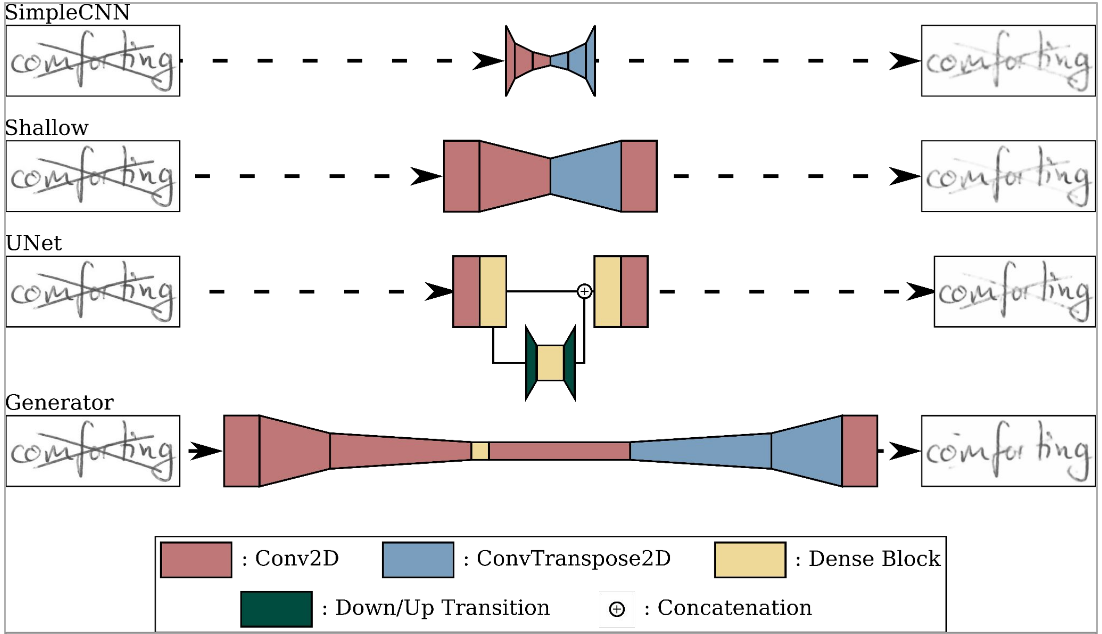


Fig.: Schematic overview over the four architectures, examined in a paired setting.

Model name	Parameter count
SimpleCNN	28 065
Shallow	154 241
UNet	181 585
Generator	1 345 217
Attribute-guided CycleGAN [1]	8 217 604

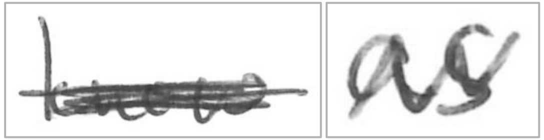
[1] Heil, R., Vats, E., Hast, A. (2021). Strikethrough Removal from Handwritten Words Using CycleGANs. ICDAR 2021

Datasets

- focus on synthetic data for training
  - ➢ genuine paired strikethrough data not easily obtained from conventional manuscripts
- evaluation on genuine data

- segmentation-based
- greyscale
- background removed

Datasets

Dataset	**IAM$_{synth}$**	**Dracula$_{real}$**	**Dracula$_{synth}$**
General Info	subset of IAM + synthetic strikethrough	handwritten copy of a portion of Bram Stoker's Dracula write → scan → strike through → scan → align	clean words from Dracula$_{real}$ train + synthetic strikethrough 5 sets of random strikethrough stroke augmentations per word
writers	multi (no set overlap)	single	single
# train	3066	126	5 x 126 and 630
# validation	273	126	N/A
# test	819	378	N/A
samples			

Experiments

1. Train on IAM_{synth} — test on IAM_{synth}
   ➢ base comparison with [1]

2. Train on IAM_{synth} — test on $Dracula_{real}$
   ➢ how well do the synthetic multi-writer models perform on (unseen) genuine single-writer data?

3. Train on individual sets of $Dracula_{synth}$ — test on $Dracula_{real}$
   ➢ what performance can be achieved with few (126) writer-specific synthetic samples?

4. Train on aggregated sets of $Dracula_{synth}$ — test on $Dracula_{real}$
   ➢ can results from 3. be improved by combining the sets?
   (→ same unique words images but larger variation in strikethrough strokes)

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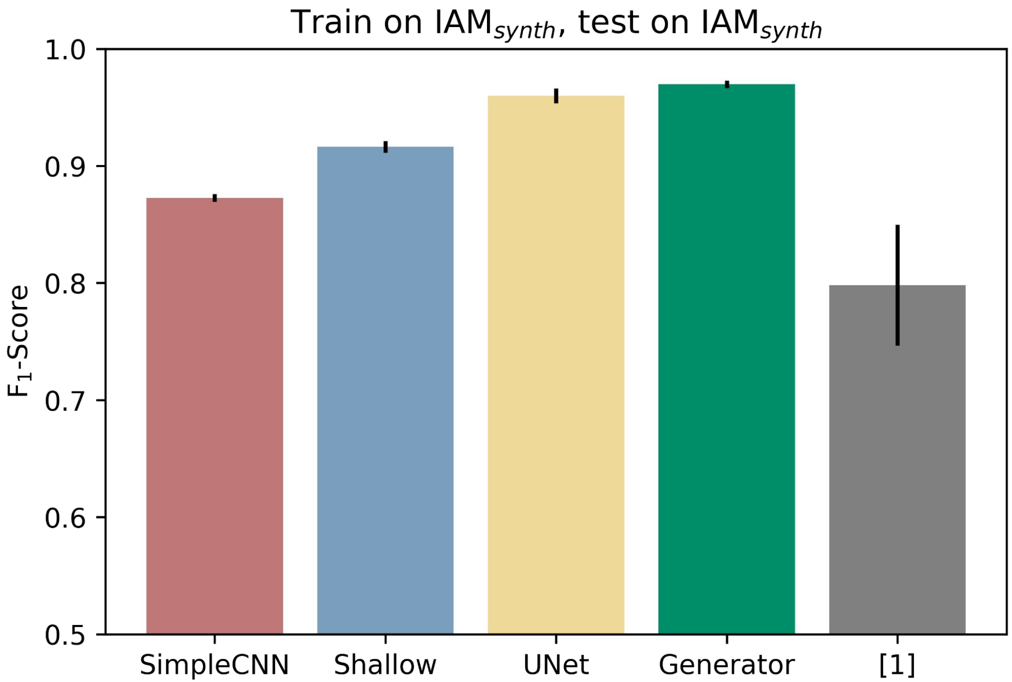
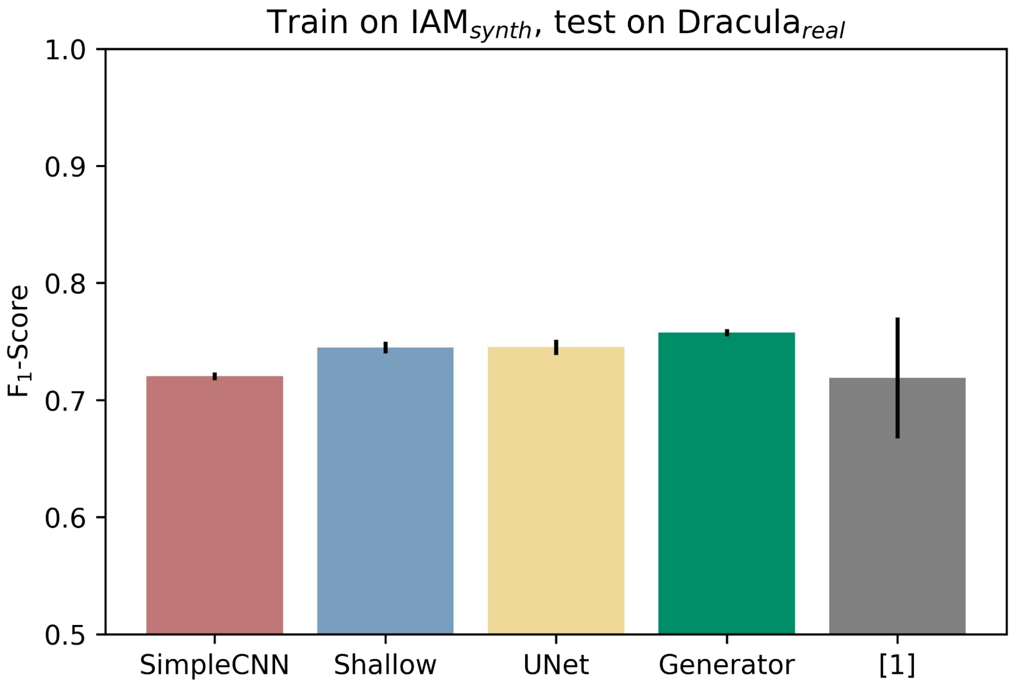
1. Train on IAM_{synth} — Test on IAM_{synth}



base comparison with [1]:

→ paired approaches outperform attribute-guided CycleGAN

2. Train on IAM_{synth} — Test on $Dracula_{real}$



How well do the synthetic multi-writer models perform on (unseen) genuine single-writer data?

→ clear drop in performance

→ overall very similar performance across models

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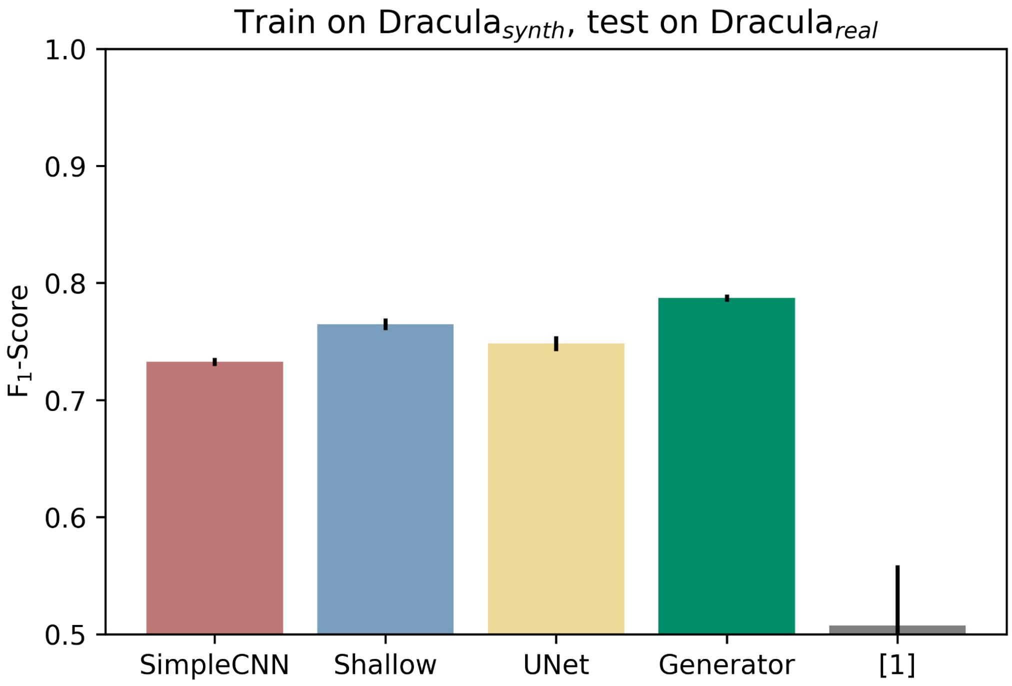
3. Train on sets of Dracula$_{synth}$ — Test on Dracula$_{real}$



What performance can be achieved with few (126) writer-specific synthetic samples?

→ paired approaches outperform their IAM$_{synth}$ counterparts
→ drastic performance drop for attribute-guided CycleGAN

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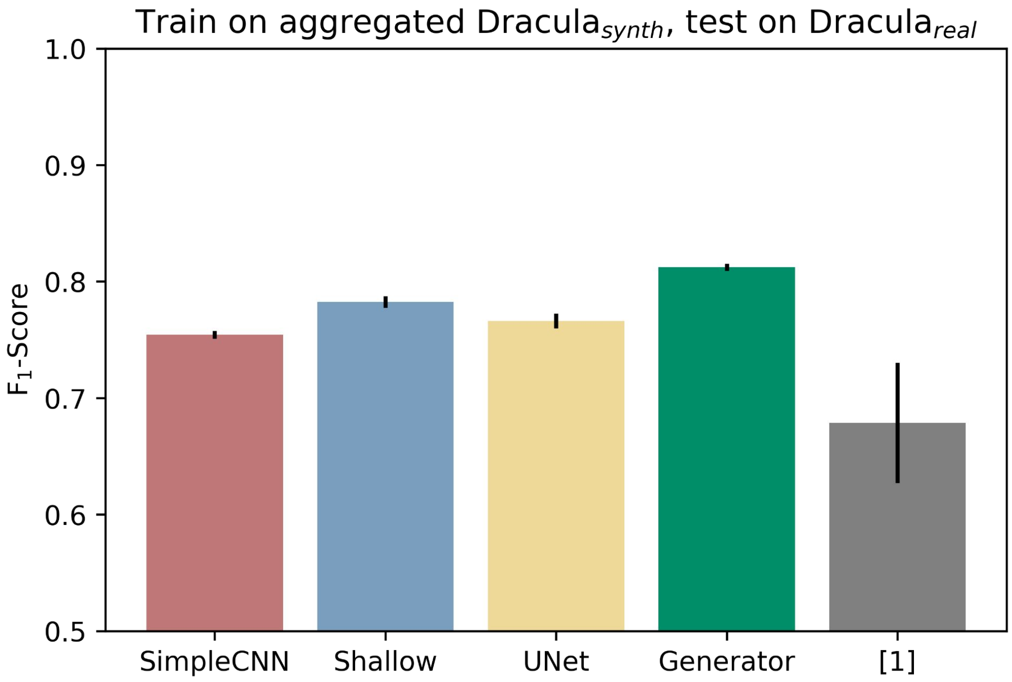
4. Train on aggregated Dracula$_{synth}$ — Test on Dracula$_{real}$



Can results from 3. be improved by combining the sets?

→ modest but consistent improvement for paired approaches
→ substantial improvement for attribute-guided CycleGAN

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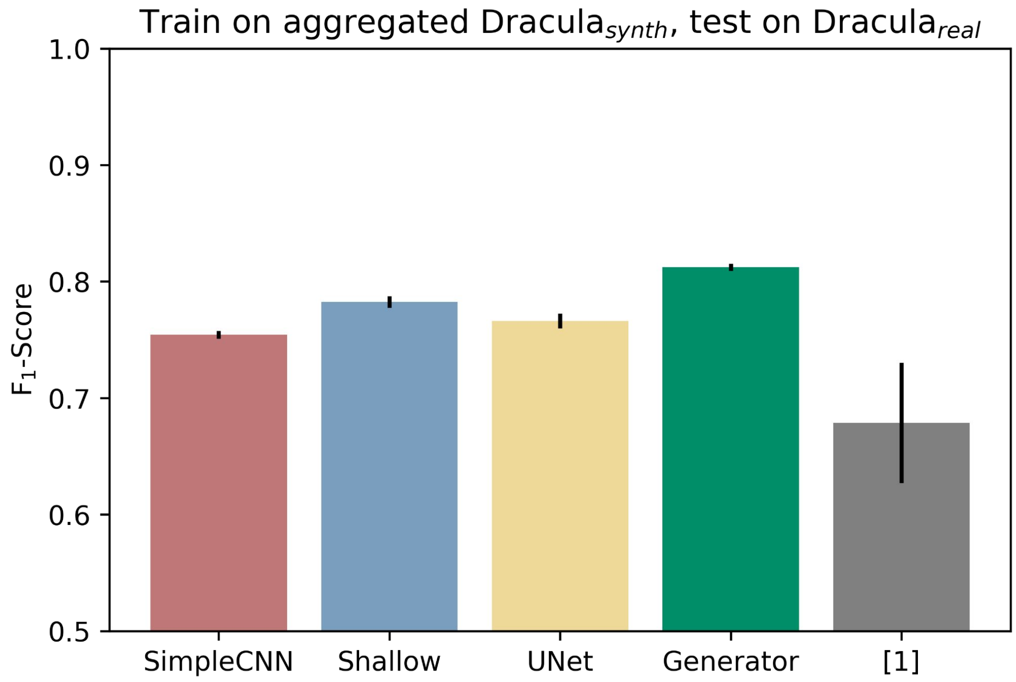
4. Train on aggregated Dracula$_{synth}$ — Test on Dracula$_{real}$



Can results from 3. be improved by combining the sets?

Future work: impact of increasing the number of unique word images in train set

Qualitative Results (trained on aggregated Dracula$_{synth}$)

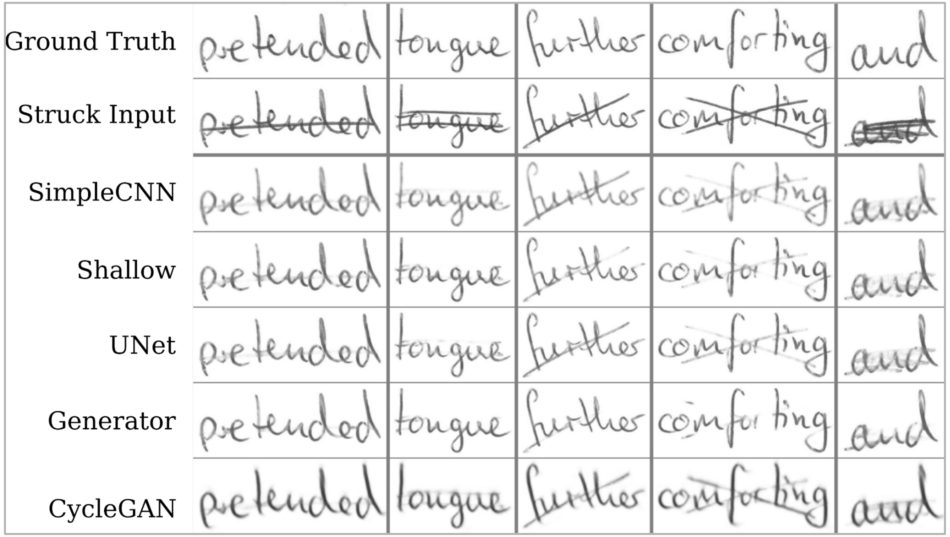


Fig.: Cherry-picked examples. Mean greyscale images, averaged over output from 30 separate models each.

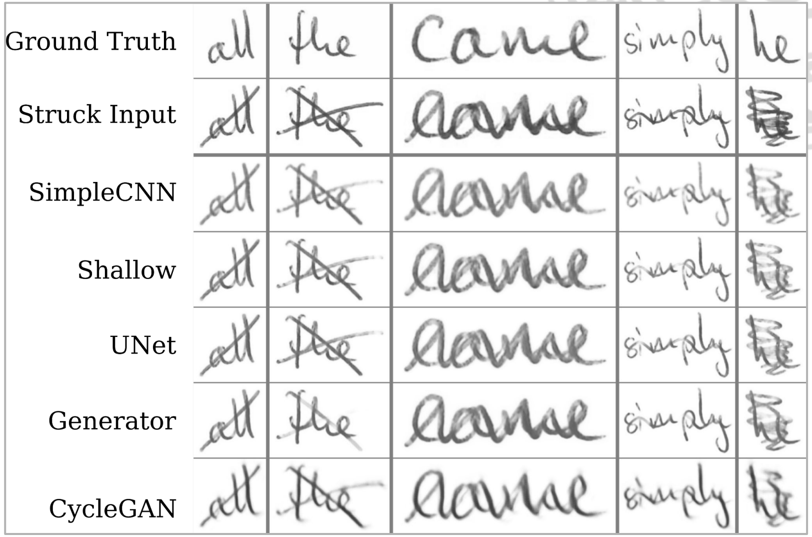


Fig.: Lemon-picked examples. Mean greyscale images, averaged over output from 30 separate models each.

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Conclusions

1. paired approaches outperform attribute-guided CycleGAN
    - general cleaning performance
    - model size
2. writer-specific models outperform multi-writer in domain
    - future work: impact of finetuning from multi to single-writer
3. varying difficulty of stroke types
    - most challenging: zigzag, wave and scratch
    - future work: focus efforts on challenging strokes

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For links to our code and datasets, please see Appendix A of our paper!

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