Style Augmentation: Data augmentation via Style Randomization

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Style Transfer[1]

- Combining a content image and a style image into a stylized image
- Content Image: Typically a photograph
- Style image: Typically a painting

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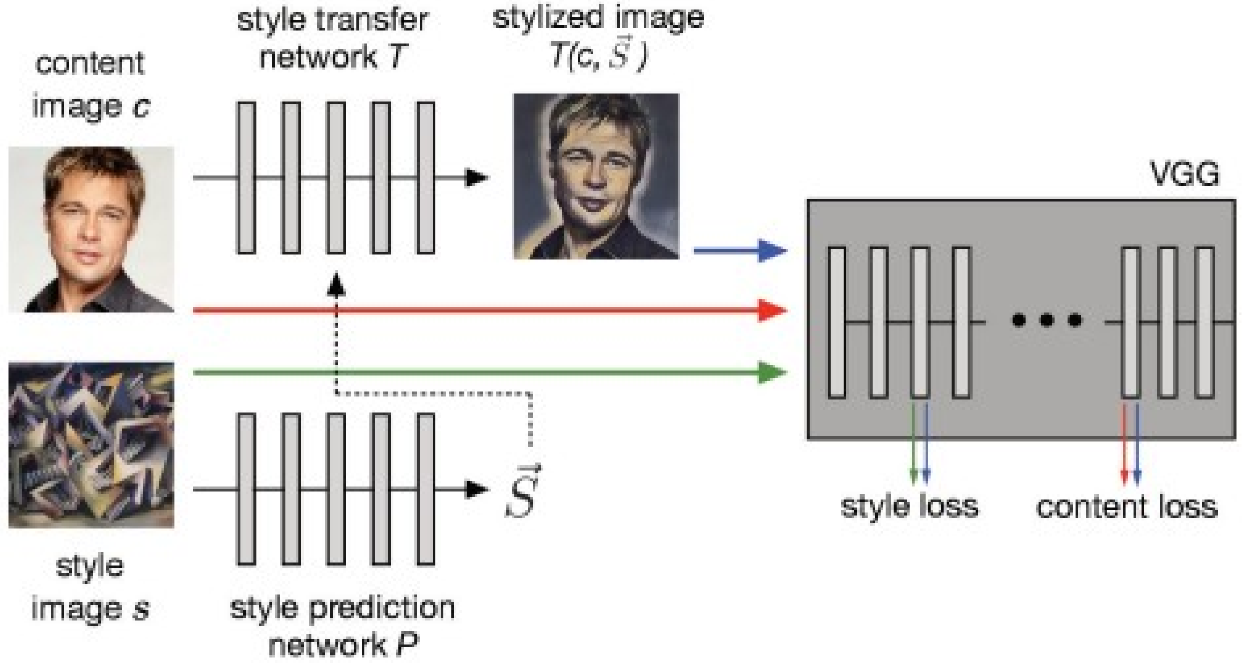
Content Style Stylized image

1. Exploring the structure of a real-time, arbitrary neural artistic stylization network. G. Ghiasi et all.

Style Transfer

- Compute style and content loss from pretrained loss network

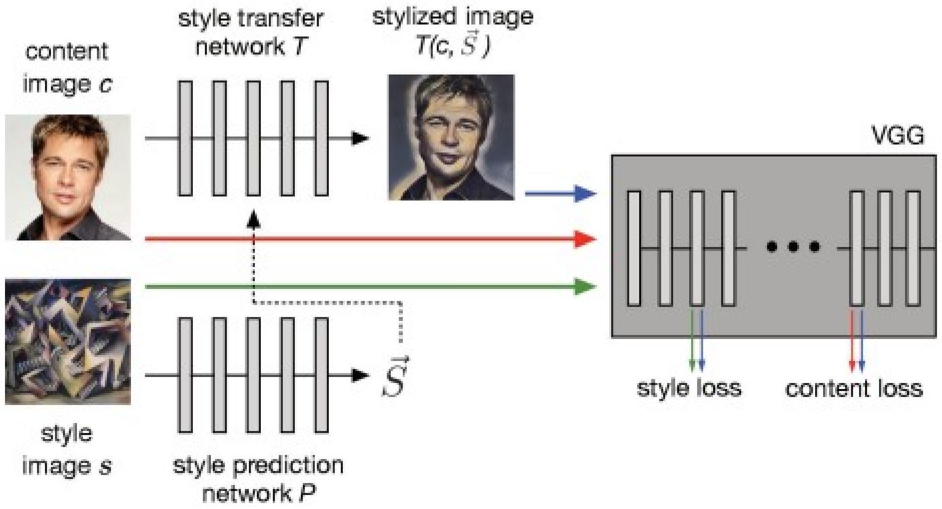
- Content: related to high level features
- Style: related to low level features



Style Loss

- Content
  - Higher level features of pretrained recognition system
  - Similar content: close high level features in Euclidean space

- Style
  - Low level features of pretrained recognition system
  - Similar style: low level features share same spatial statistics
  - Spatial statistics can be represented by a Gram matrix of correlations across filters



Style Transfer Loss

Content Loss:

Content Loss: $L_c = \sum_{i \in C} || f_i(x) - f_i(c) ||_F^2$

Style Loss:

Style Loss: $L_S = \sum_{i \in S} || G[f_i(x)] - G[f_i(s)] ||_F^2$

Total Loss:

Total Loss: $L_c(x, c) + \lambda_s L_s(x, s)$

x = stylized image, c = content image, s = style image, f = pretrained network

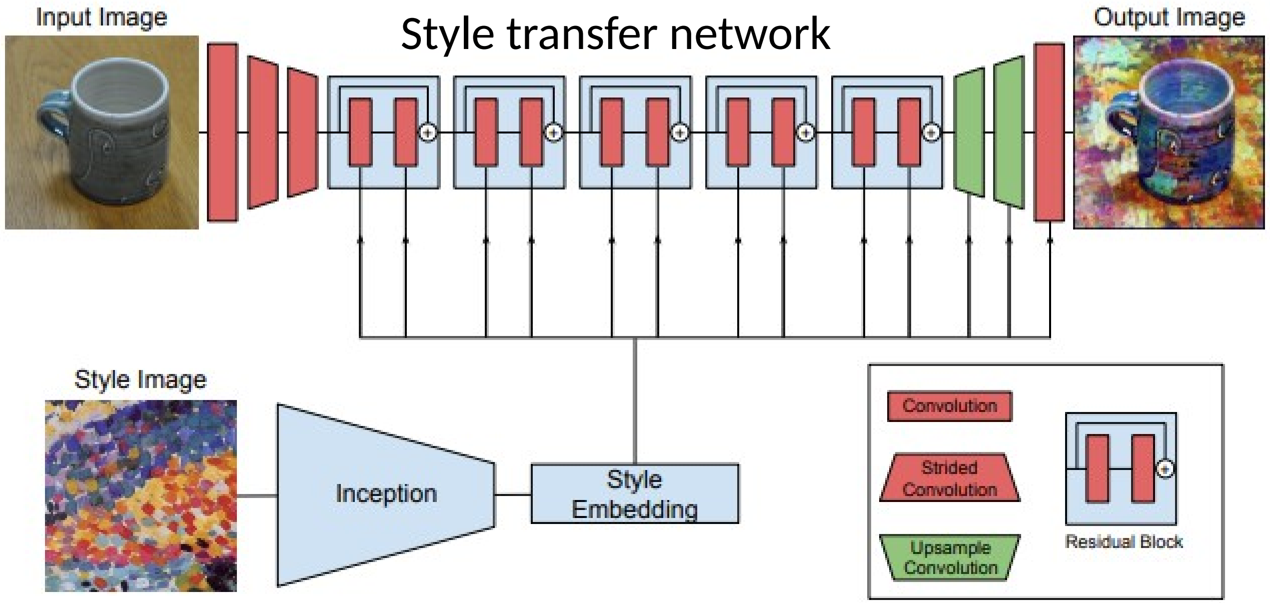
= relative weight of style loss

λ_s = relative weight of style loss

Integration of both networks

- Style embedding
  - Vector of length 100

- Conditional instance normalization:
  - Shift and rescale activation channels
  - Normalize feature maps with style embedding
    - $x' = \gamma \frac{(x-\mu)}{\sigma} + \beta$
    - μ, σ: mean and std from feature map
    - γ, β: linear transformation obtained from style embedding

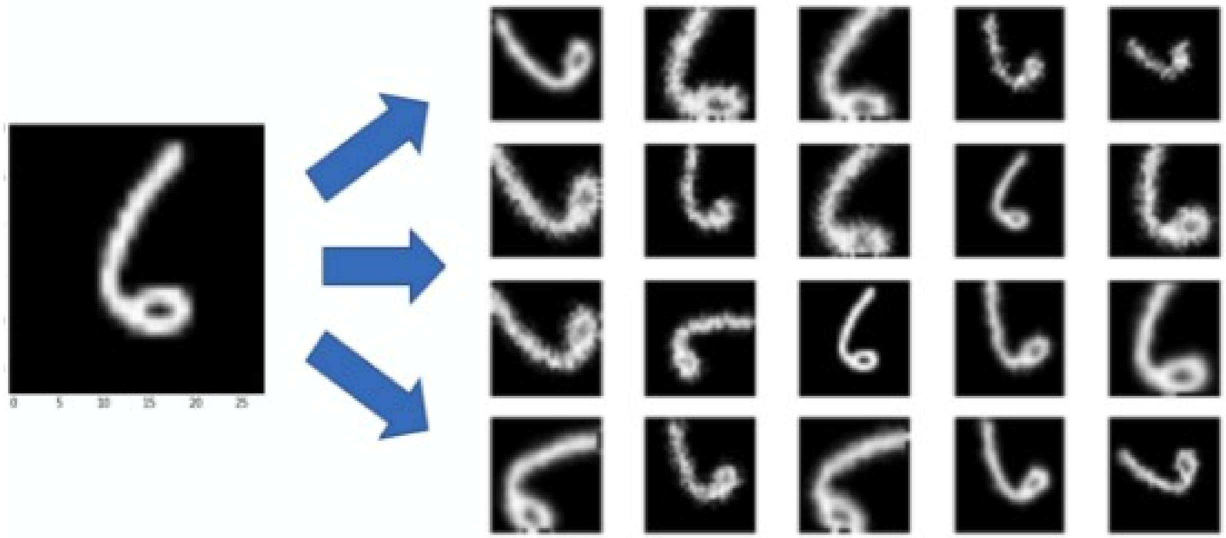


Style prediction network

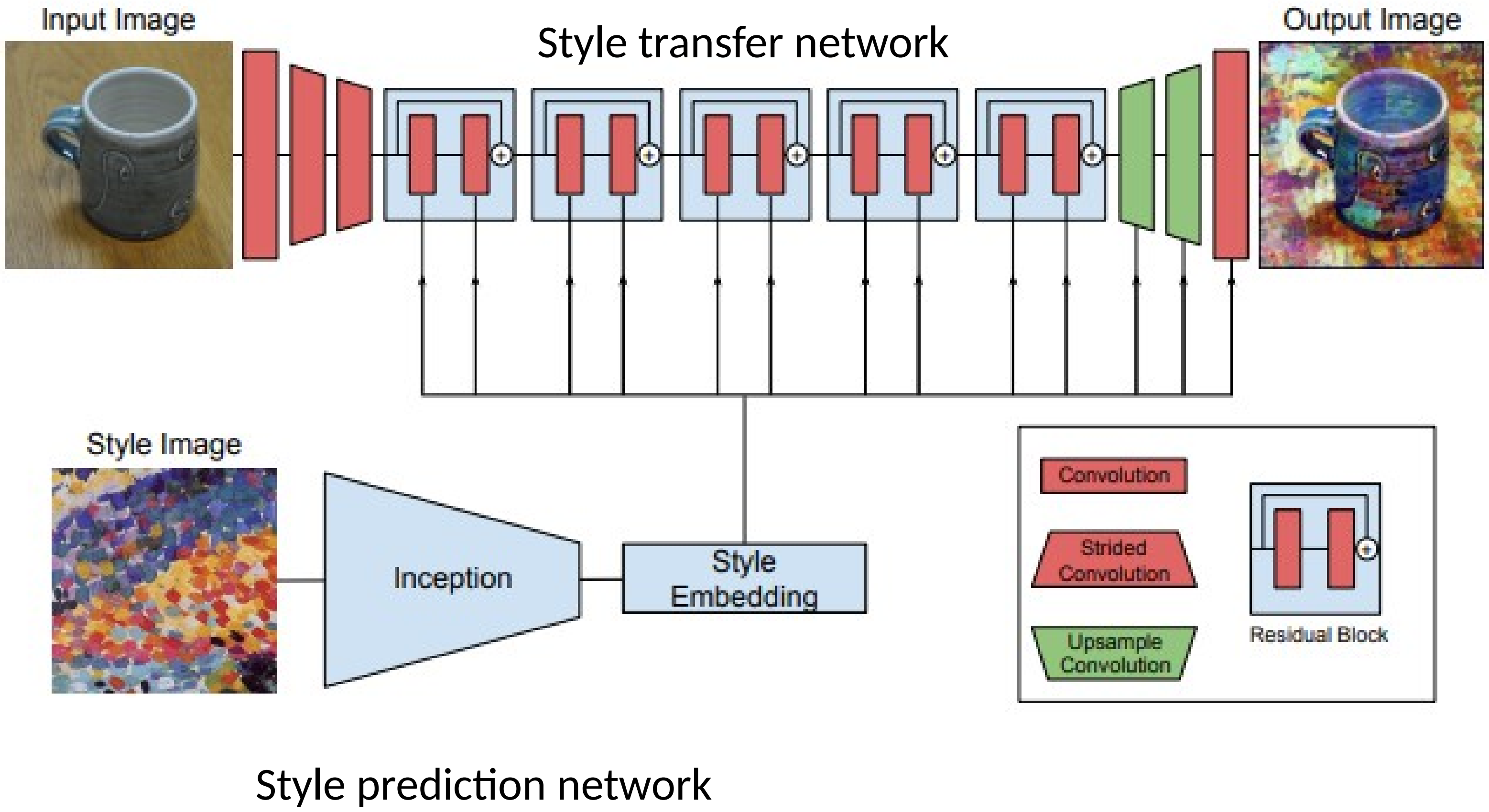
Style Transfer

Style transfer for data augmentation

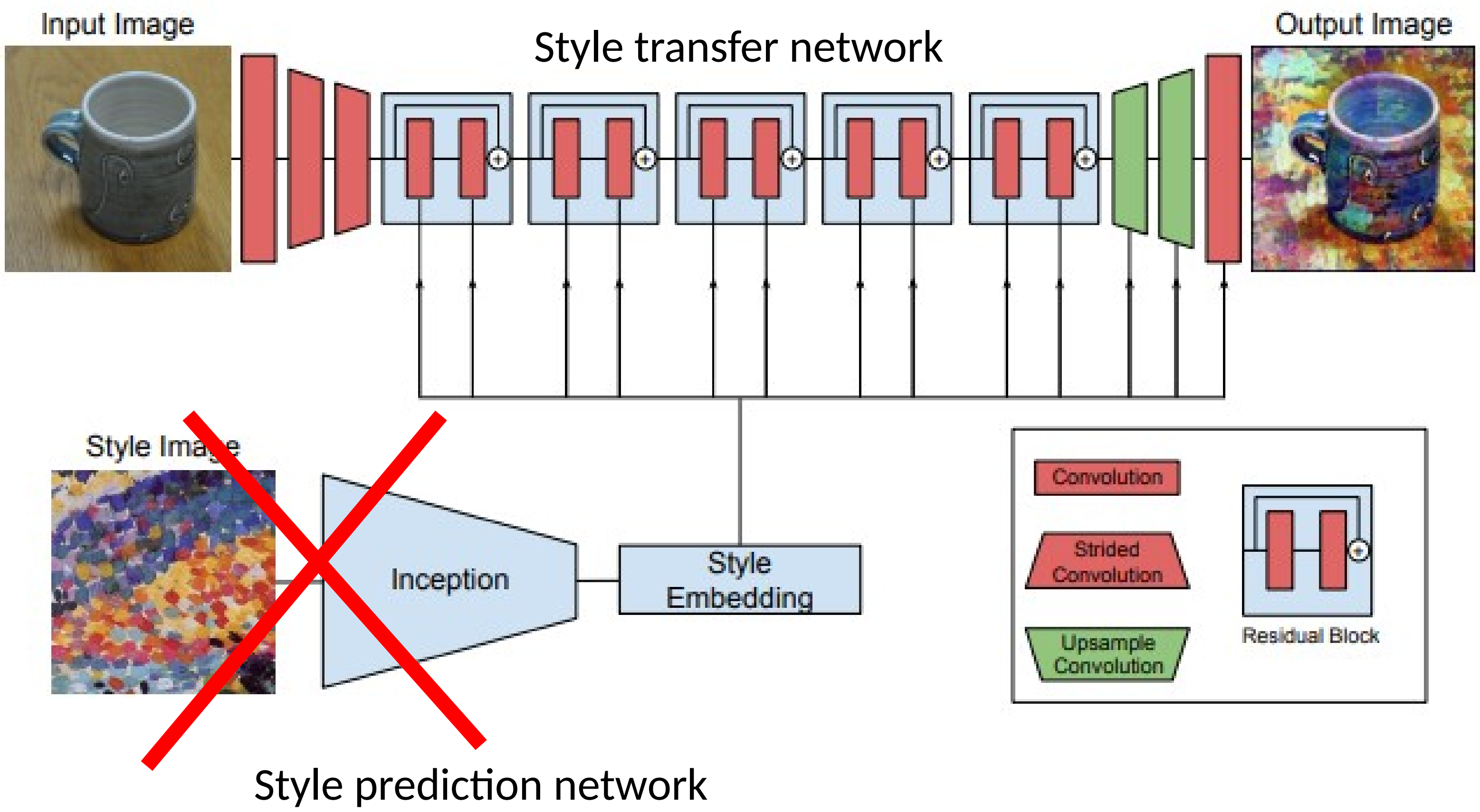
- Data augmentation: Creating new training samples from existing ones
- Commonly used:
  - Flipping, Translations, Scaling, Blurring etc.
- Style Transfer:
  - Randomizing color, texture and contrast
  - Preserving geometry



Style transfer for data augmentation



Style transfer for data augmentation



Random style embedding

- Sampling style embedding from probability distribution
  - Normal distribution with mean and covariance of Painter By Number style dataset
- Strength of augmentation
  - Mix style embedding with embedding of content image

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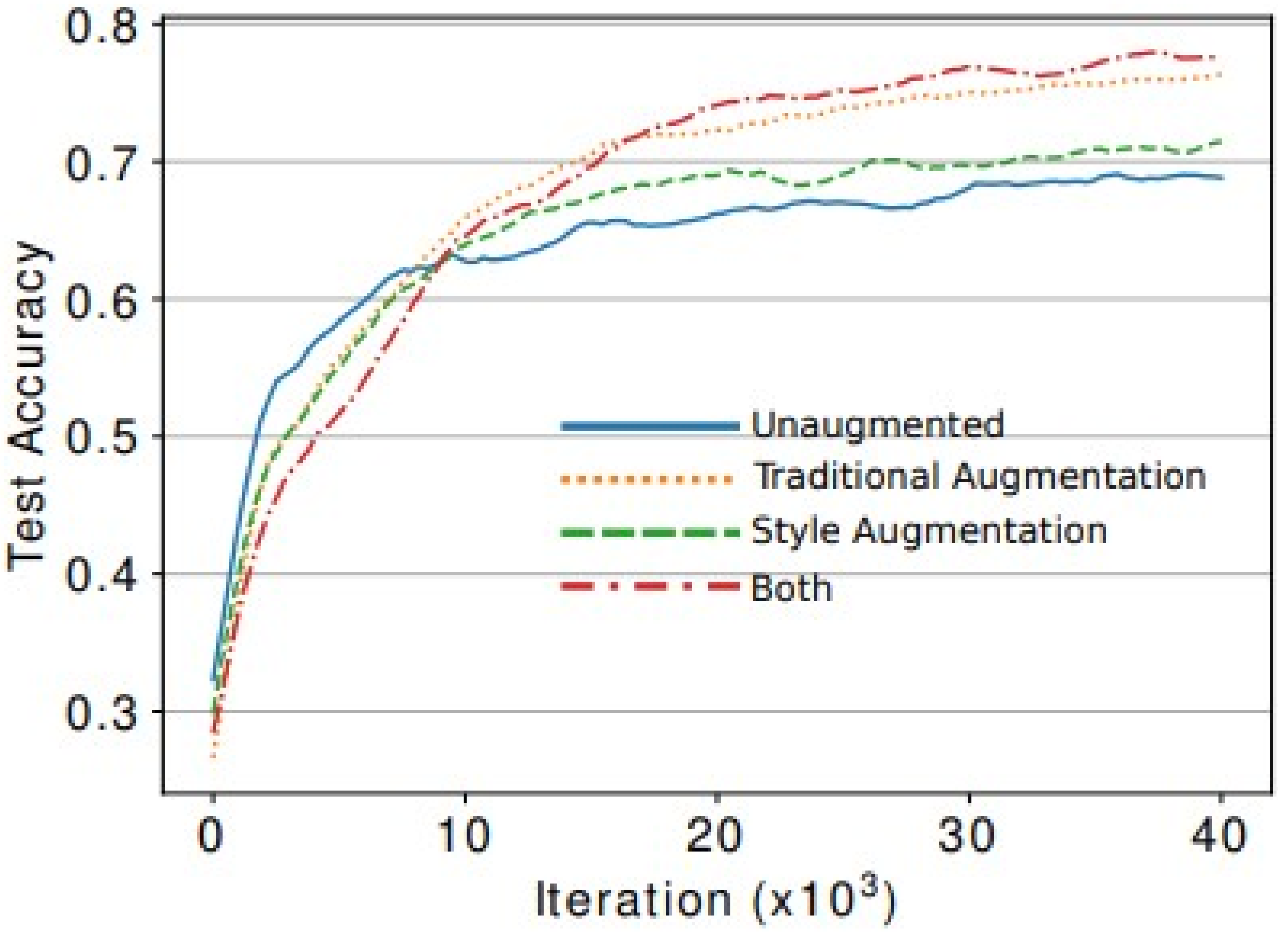
$$z = \underbrace{\alpha \mathrm{N}(\mu, covariance)}_{\text{Style embedding}} + (1-\alpha)\underbrace{P(c)}_{\text{Style of content image}}$$

Experiments

- Use random style transfer as augmentation technique for
  - Image classification
  - Cross-domain classification
  - Depth estimation
- Traditional augmentation as reference
  - Horizontal flipping, small rotations, zooming, random erasing, shearing, greyscale conversion and perturbations of hue, brightness and contrast
- Hyperparameter search
  - Augmentation ratio
  - Augmentation strength (α)

Image classification

- STL-10 dataset
- 10 classes: animals and vehicles

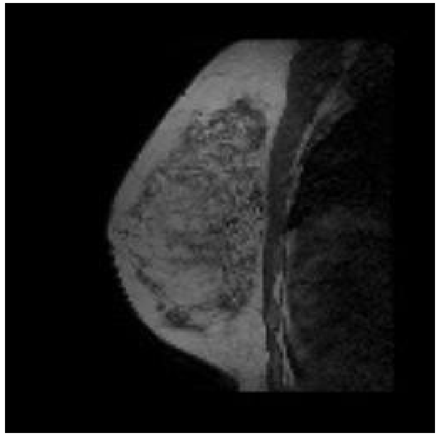


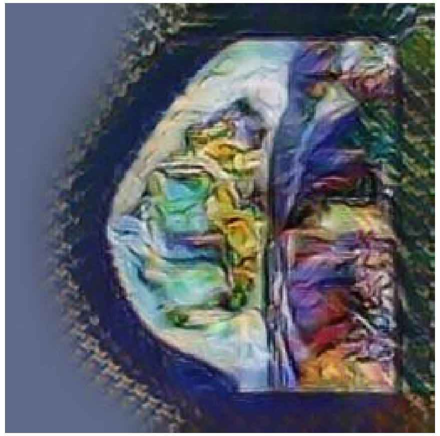
Cross-domain classification

- Office dataset with 3 domains: Amazon, Webcam and DSLR

Task	Model	Augmentation Approach			
		None	Trad	Style	Both
$AW \rightarrow D$	InceptionV3	0.789	0.890	0.882	**0.952**
	ResNet18	0.399	0.704	0.495	**0.873**
	ResNet50	0.488	0.778	0.614	**0.922**
	VGG16	0.558	0.830	0.551	**0.870**
$DW \rightarrow A$	InceptionV3	0.183	0.160	0.254	**0.286**
	ResNet18	0.113	0.128	0.147	**0.229**
	ResNet50	0.130	0.156	0.170	**0.244**
	VGG16	0.086	0.149	0.111	**0.243**
$AD \rightarrow W$	InceptionV3	0.695	0.733	0.767	**0.884**
	ResNet18	0.414	0.600	0.424	**0.762**
	ResNet18	0.491	0.676	0.508	**0.825**
	VGG16	0.465	0.679	0.426	**0.752**

Stylized Images

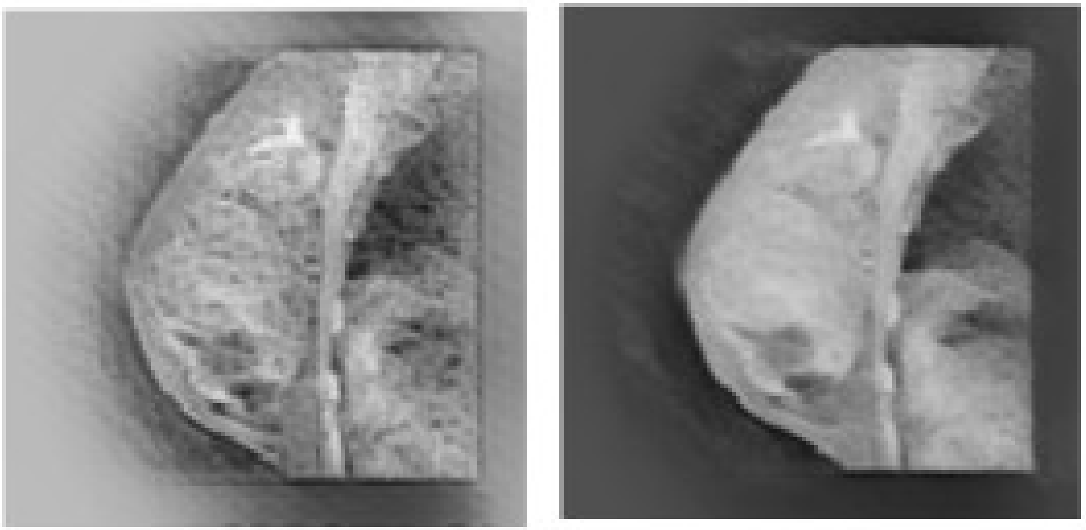




Application

- Cross-domain adaptation for MRI Breast Segmentation
  - T1 → T2
- Use trained network from data augmentation paper
  - Greyscale → RGB → Greyscale
  - Apply same random style on each slice of 3D volume

T2-scan



Restyled images

Github Codes

- Style Augmentation: Data augmentation via Style Randomization: https://github.com/philipjackson/style-augmentation

- Exploring the structure of a real-time, arbitrary neural artistic stylization network: https://github.com/tensorflow/magenta/tree/master/magenta/models/arbitrary_image_stylization