Augmentacja danych

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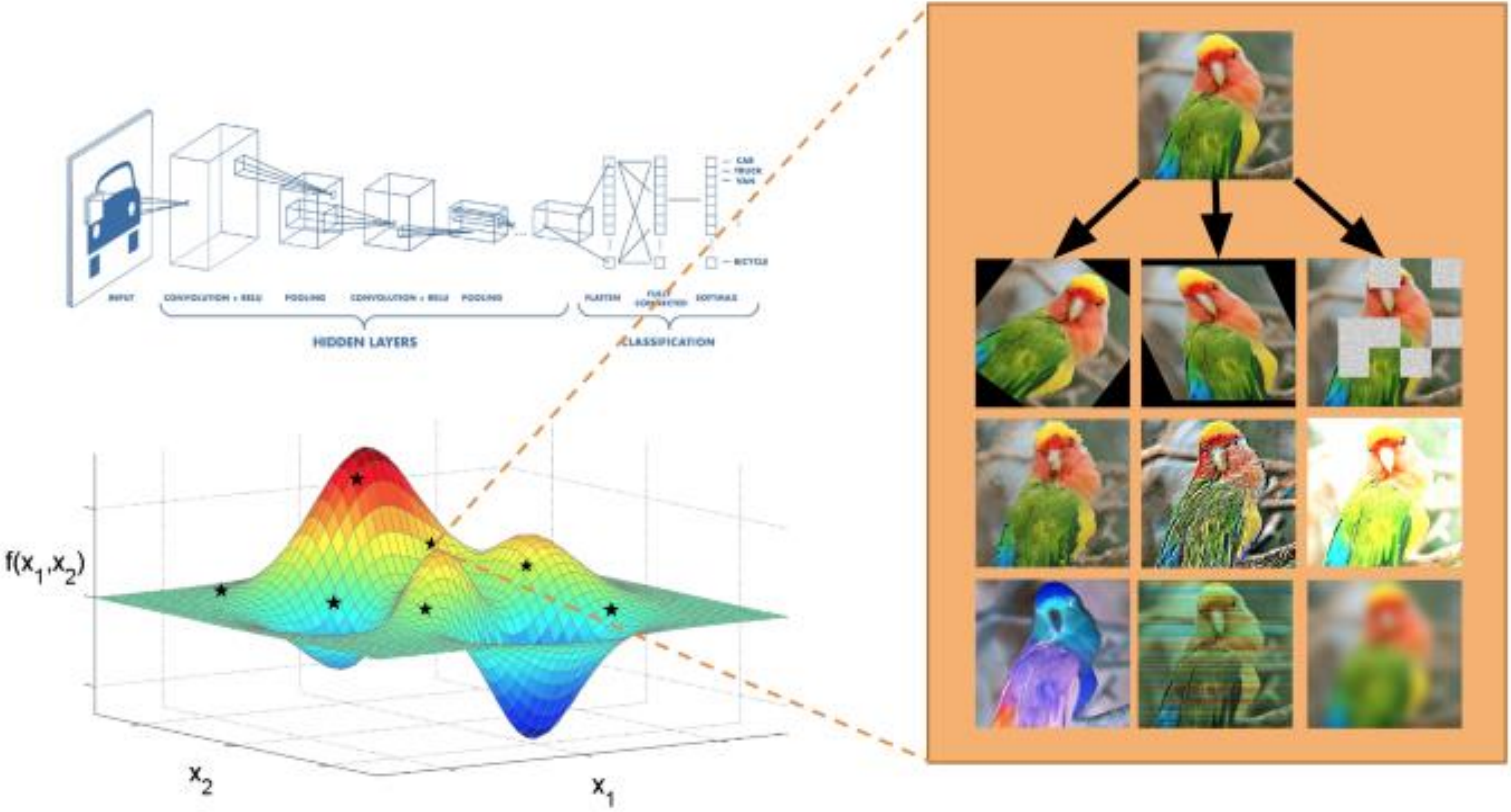

https://blog.insightdatascience.com/automl-for-data-augmentation-e87cf692c366

Three ways to improve data

1 - Collect more

- expensive
- requires manual labor

2 - Synthesize

- complicated
- might not truly represent the real data

3 - Augment

- simple
- but finding a good augmentation strategy takes lots of trial & error (**=time of AI engineers**)

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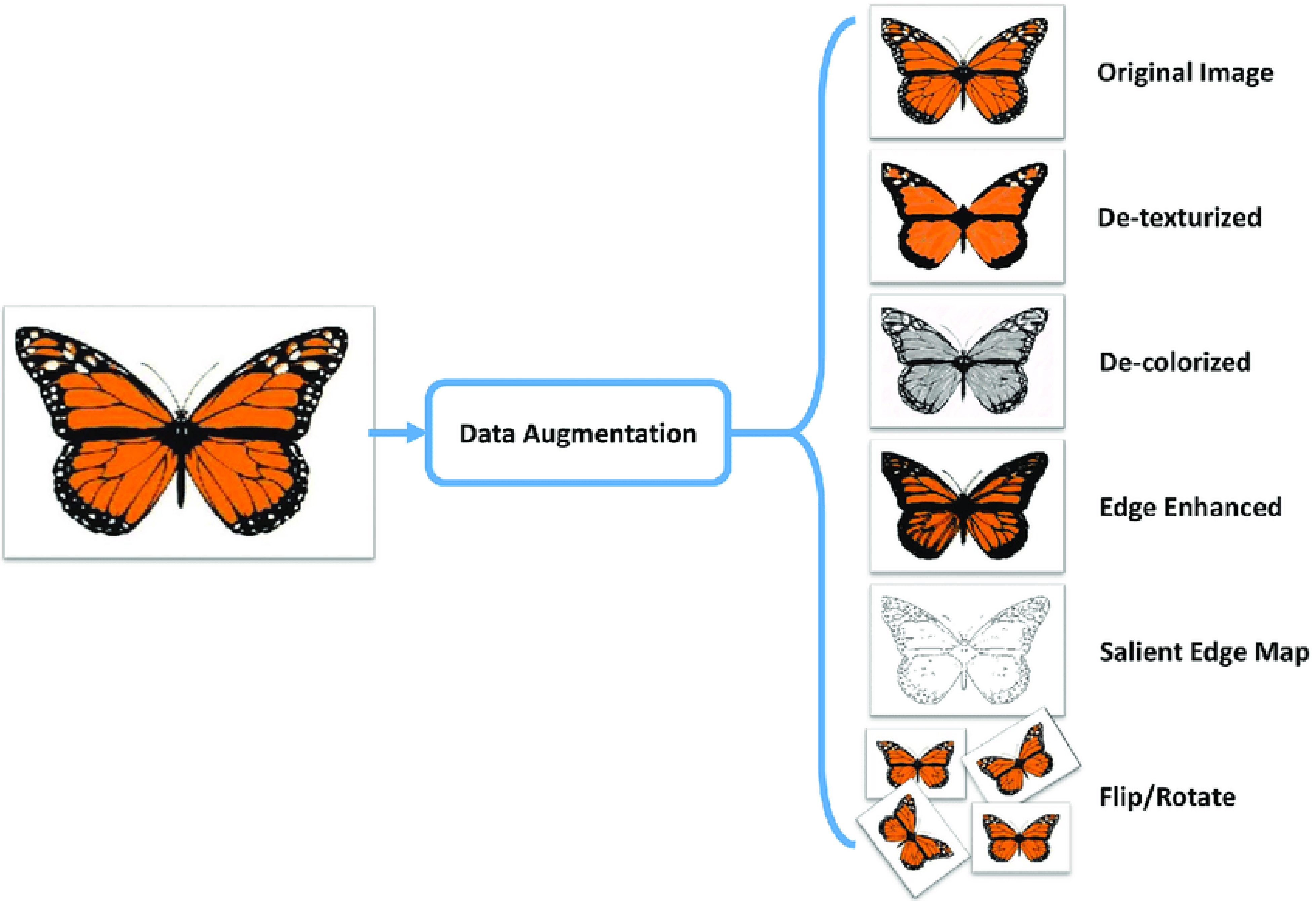
6.2. Data augmentation

rotacje, odbicia lustrzane, skalowanie tj. RandomRotate90, Flip, Compose, Normalize, RandomResizedCrop

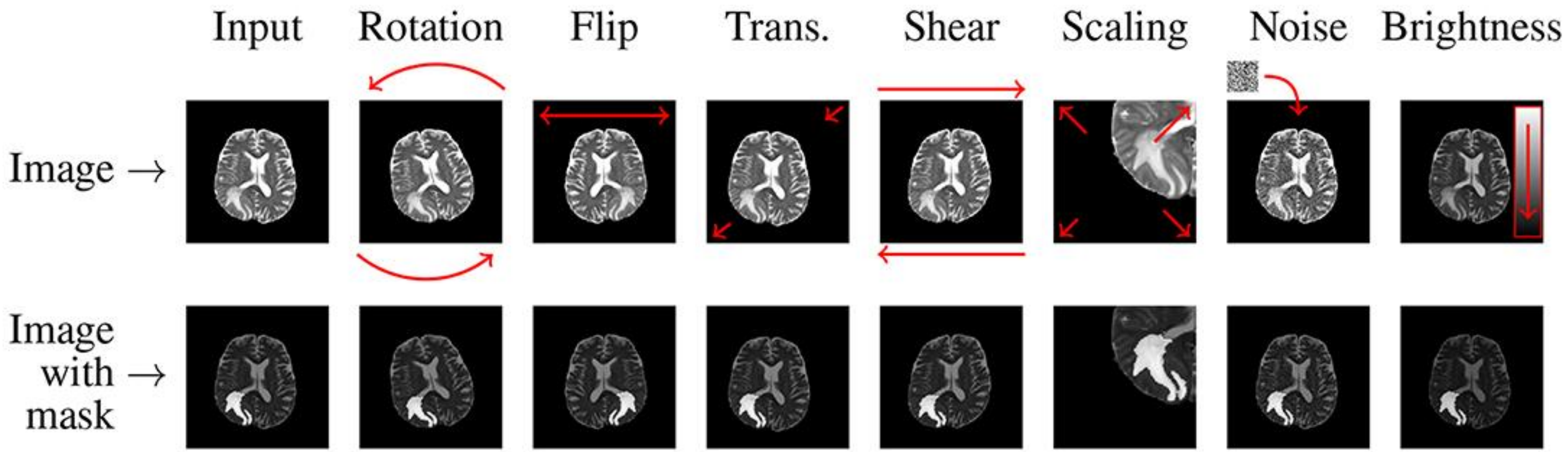
```
# data augmentation on both tile level and big image level

augmentation_pipeline_before_splitting = A.Compose([
    A.HorizontalFlip(p=0.6),
    A.VerticalFlip(p=0.6),
    A.OneOf([
        A.RandomContrast(),
        A.RandomGamma(),
        A.RandomBrightness(),
        A.RGBShift()
         ], p=0.9),
    A.ElasticTransform(alpha=120, sigma=120 * 0.05, alpha_affine=120 * 0.03, p=0.5),
    A.GridDistortion(p=0.5),
    A.OpticalDistortion(distort_limit=2, shift_limit=0.5, p=0.5),
],p=1)


augmentation_pipeline_after_splitting = A.Compose([
    A.Flip(p=0.7),
    A.RandomRotate90(p=1.0),
], p=1)
```

Base Augmentations

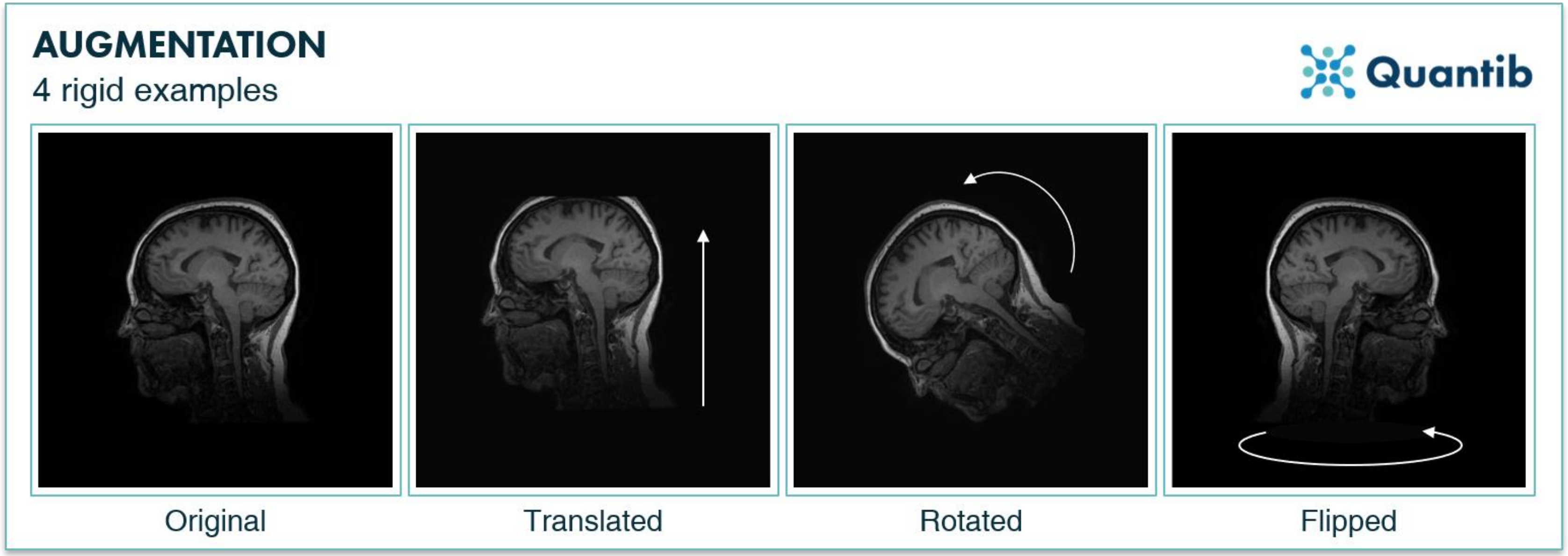
https://blog.insightdatascience.com/automl-for-data-augmentation-e87cf692c366

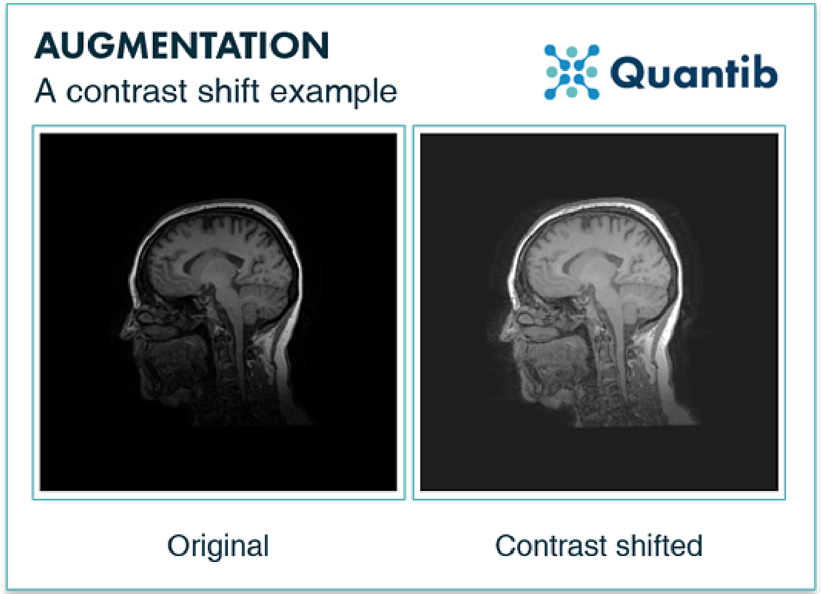


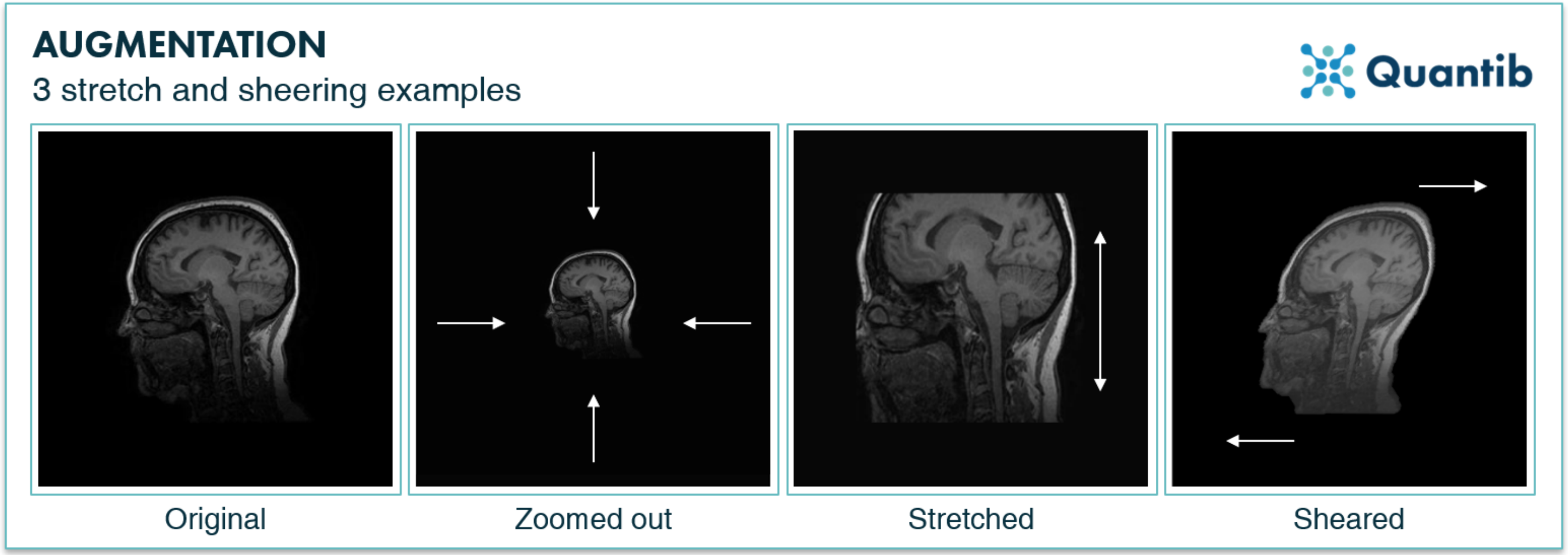
www.researchgate.net/figure/Data-augmentation-using-semantic-preserving-transformation-for-SBIR_fig2_319413978

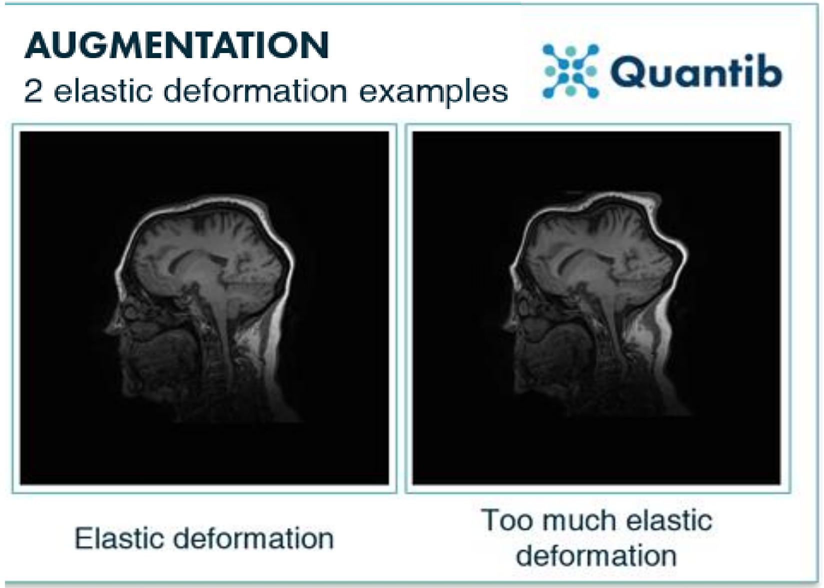


https://www.frontiersin.org/articles/10.3389/fncom.2019.00083/full

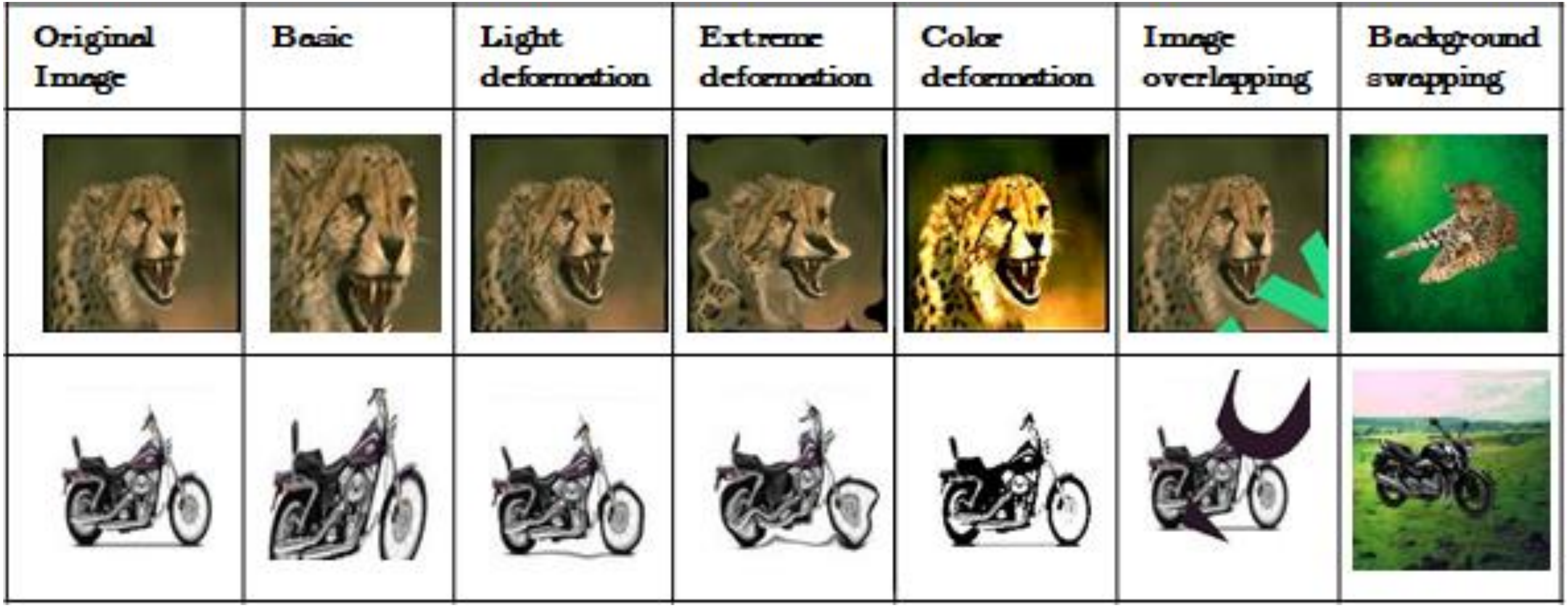








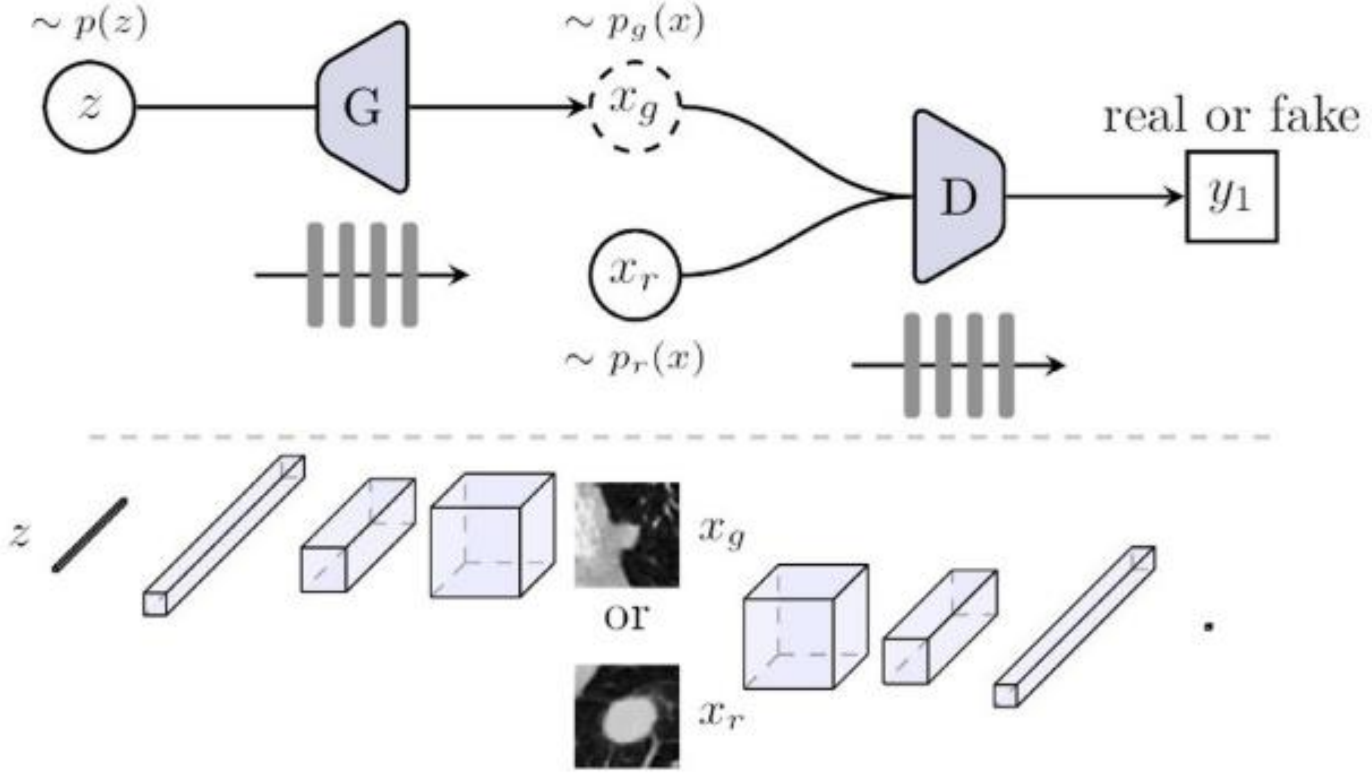
www.quantib.com/blog/image-augmentation-how-to-overcome-small-radiology-datasets



https://medium.com/@mcr222/data-augmentation-benchmark-for-deep-learning-2db712c6eb3e

Vanilla GAN

$$\mathcal{L}_D^{GAN} = \max_D \mathbb{E}_{x_r \sim p_r(x)}[\log D(x_r)] + \mathbb{E}_{x_g \sim p_g(x)}[\log(1 - D(x_g))],$$
$$\mathcal{L}_G^{GAN} = \min_G \mathbb{E}_{x_g \sim p_g(x)}[\log(1 - D(x_g))].$$



$z \in \mathbb{R}^{n\times1\times1}$

$x_g, x_r \in \mathbb{R}^{c\times w\times h}$

$y_1 \in \{0, 1\}$

https://www.sciencedirect.com/science/article/abs/pii/S1361841518308430

Problemy

- Brak gwarancji równowagi między treningiem G i D
  - W większości przypadków D jest mocniejsza.
  - Gradienty z D zbliżają się do zera, nie dając żadnych wskazówek dla dalszego treningu G
- Generowanie obrazów o wysokiej rozdzielczości
- Mode collapse

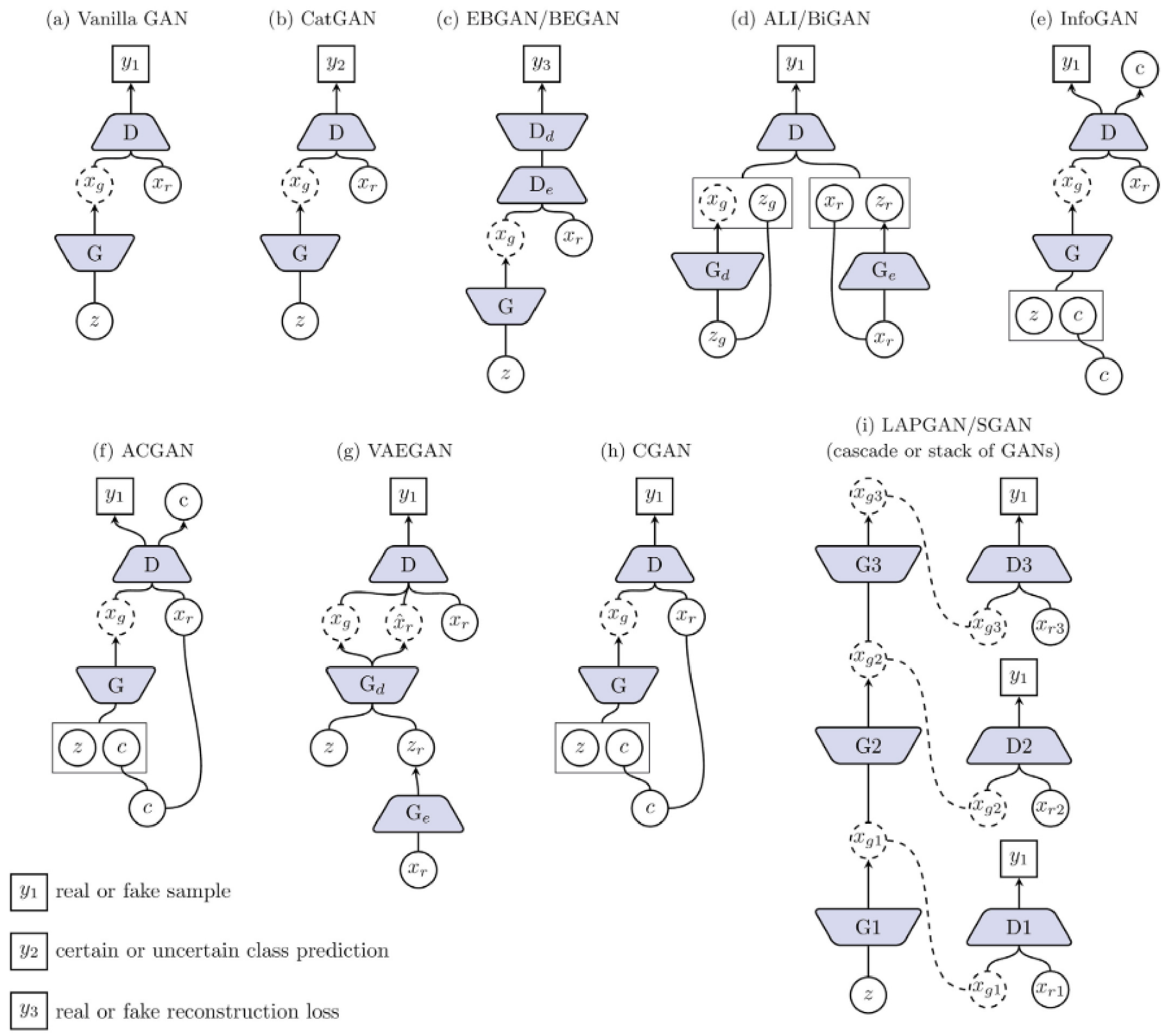


Fig. 3. A schematic view of variants of GAN. *c* represents the conditional vector. In CGAN and ACGAN, *c* is the discrete categorical code (e.g. one hot vector) that encodes class labels and in InfoGAN it can also be continuous code that encodes attributes. x_g generally refers to the generated image but can also be internal representations as in SGAN.

https://www.sciencedirect.com/science/article/abs/pii/S1361841518308430