# Data Augmentation Using GANs

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# Main Goal

Our main goal is to generate faces with specific emotions. This generated data will serve as an external data source that helps improve a classifier.

# Part A

Synthetic Data Generation by emotion transition using Generative Adversarial Networks

# The Data

FER2013

For middle stage, FER2013 dataset was chosen.

This dataset contains images of size 48x48 pixels and 7 emotion expressions: Angry, Disgust, Fear, Happy, Sad, Surprise, Neutral.

# Data Distribution

The data distribution in FER2013 dataset is:

| Emotion | Amount |
|---|---|
| Angry | 4593 |
| *Disgust | 547 |
| Fear | 5121 |
| Happy | 8989 |
| Sad | 6077 |
| Surprise | 4002 |
| Neutral | 6198 |

* - we will discuss further

# The Cycle GAN Model

The project uses CycleGAN architecture, as a method, for image-to-image style transfer.

CycleGAN - is a two way GAN, that consists of 2 *Discriminators* and 2 *Generators*.

The idea is to transfer an input from one domain to another back and forth.

# Theory Background

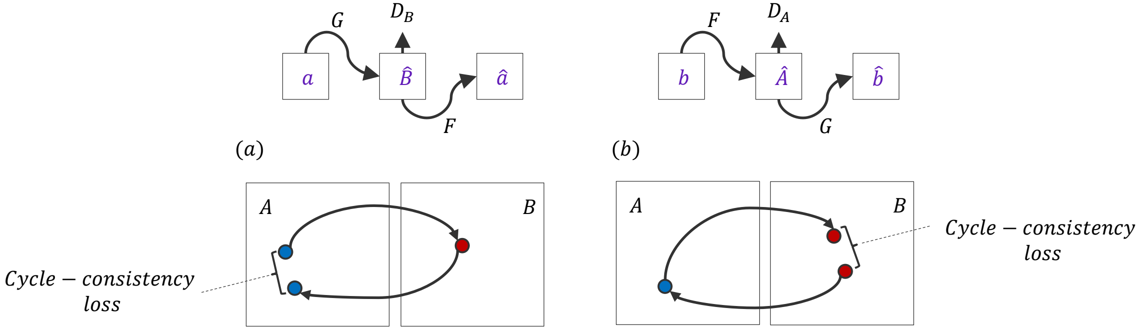
Domains A, B, mapping functions: $G{:}A\rightarrow B$, $F{:}B\rightarrow A$, associated adversarial discriminators $D_A, D_B$

$D_B$ encourages $G$ to translate $A$ into outputs indistinguishable from domain $B$, and vice versa, for $D_A$ and $F$.

To further regularize the mappings, used *two-cycle consistency loss*. The main intuition, that when translating from one domain to another and back again, the model should arrive at where it started. Two-cycle consistency loss consists of:

(a) Forward cycle-consistency: $a\rightarrow G(a)\rightarrow F(G(a))\approx a$

(b) Backward cycle-consistency: $b\rightarrow F(b)\rightarrow G(F(b))\approx b$



# Target and loss functions

- Adversarial loss:

$$\mathcal{L}_{GAN}(G, D_A, A, B) = \mathbb{E}_{a\sim p_{data}(a)}[(D_A(a) - 1)^2] + \mathbb{E}_{b\sim p_{data}(b)}\left[\left(D_A(G(b))\right)^2\right]$$

- Cycle consistency loss:

$$\mathcal{L}_{cyc}(G, F) = \mathbb{E}_{a\sim p_{data}(a)}\left[\left\|F\left(G(a)\right) - a\right\|_1\right] + \mathbb{E}_{b\sim p_{data}(b)}\left[\left\|G\left(F(b)\right) - b\right\|_1\right]$$

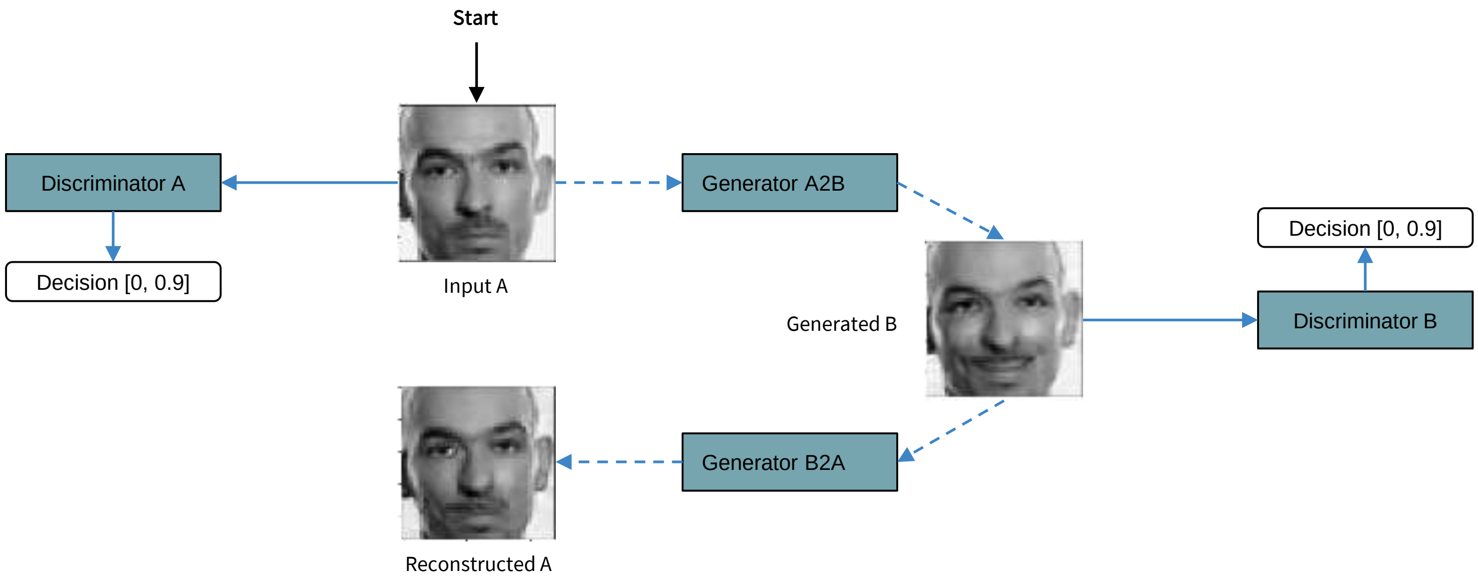
- Full objective:

$$\mathcal{L}(G, F, D_A, D_B) = \mathcal{L}_{GAN}(G, D_B, A, B) + \mathcal{L}_{GAN}(F, D_A, A, B) + \lambda\mathcal{L}_{cyc}(G, F)$$

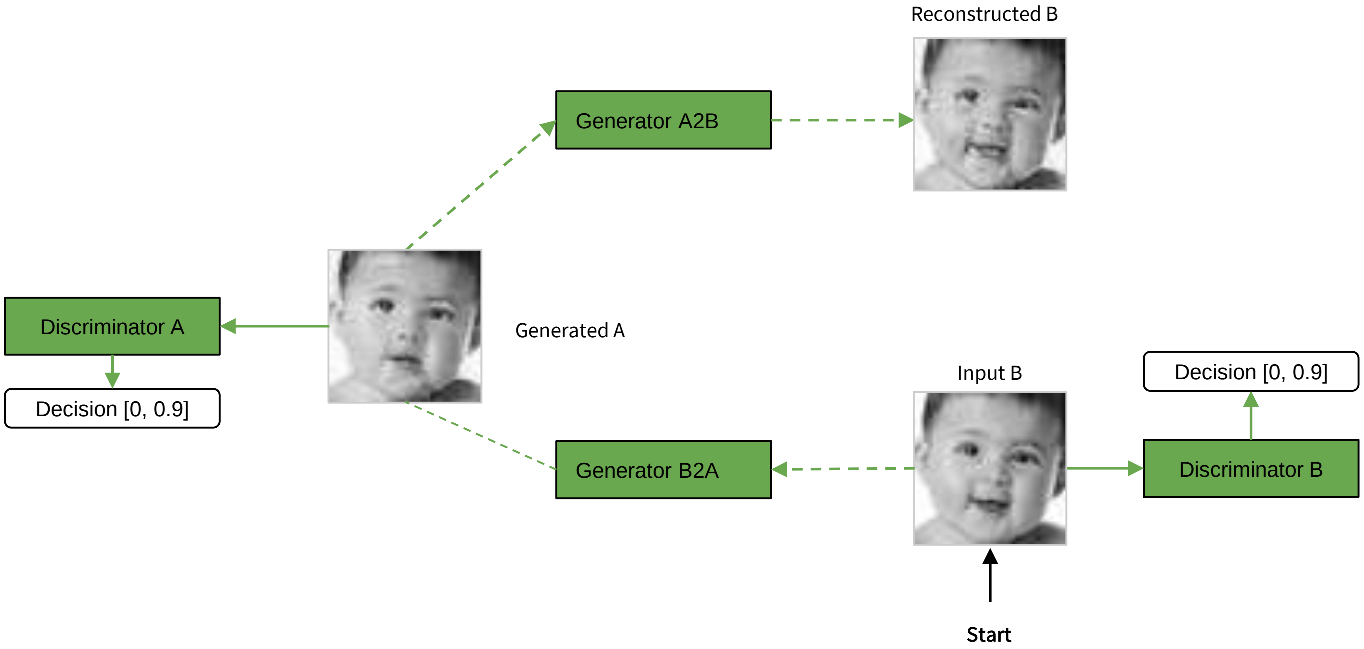
- Target function:

$$\hat{G}, \hat{F} = \arg\min_{G,F}\max_{D_A,D_B}\mathcal{L}(G, F, D_A, D_B)$$

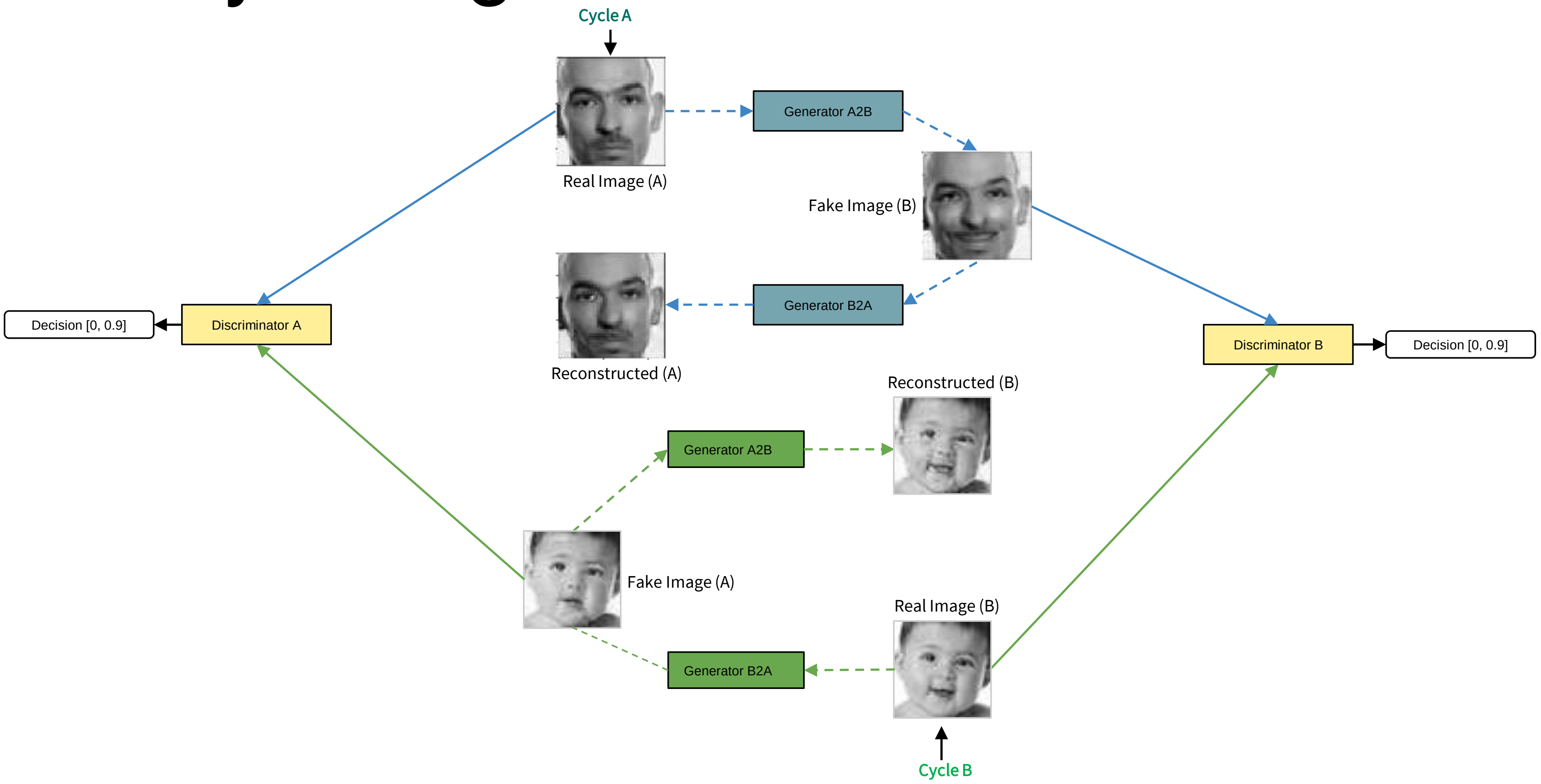
# The Model: *Forward Cycle A2B*



# The Model: *Backward Cycle B2A*



# Both cycles together



# The Architecture

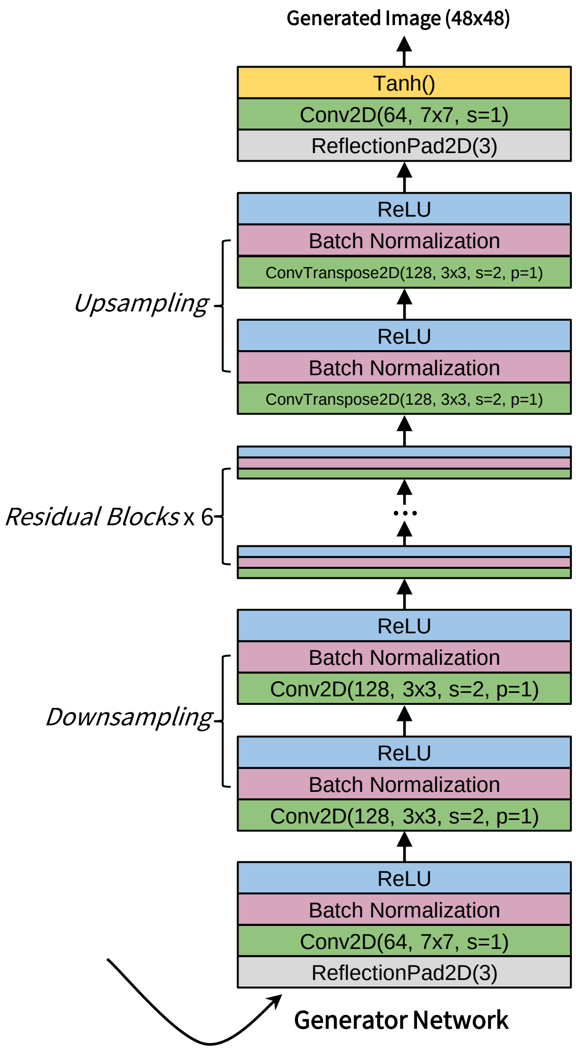
Anatomy of Cycle GAN

Generator and Discriminator

# The Networks: *Generator*

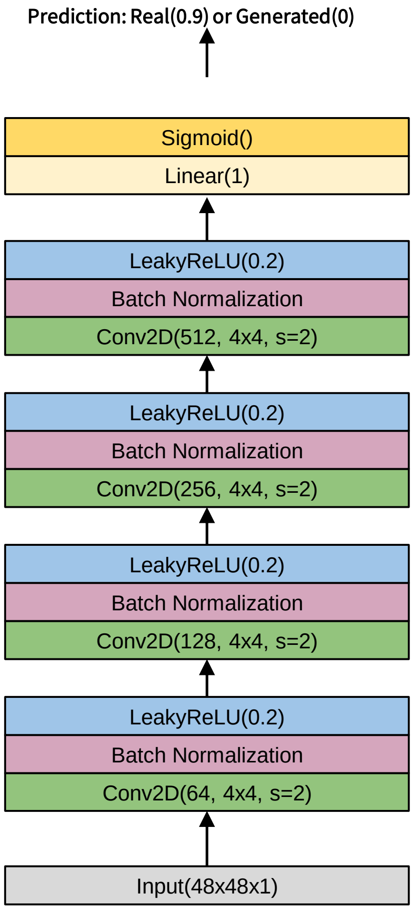
The Generator consists of 3 parts:

- Decode (downsampling)
- Transferring (6 residual blocks)
- Encode (upsampling).



# The Networks:
# *Discriminator*

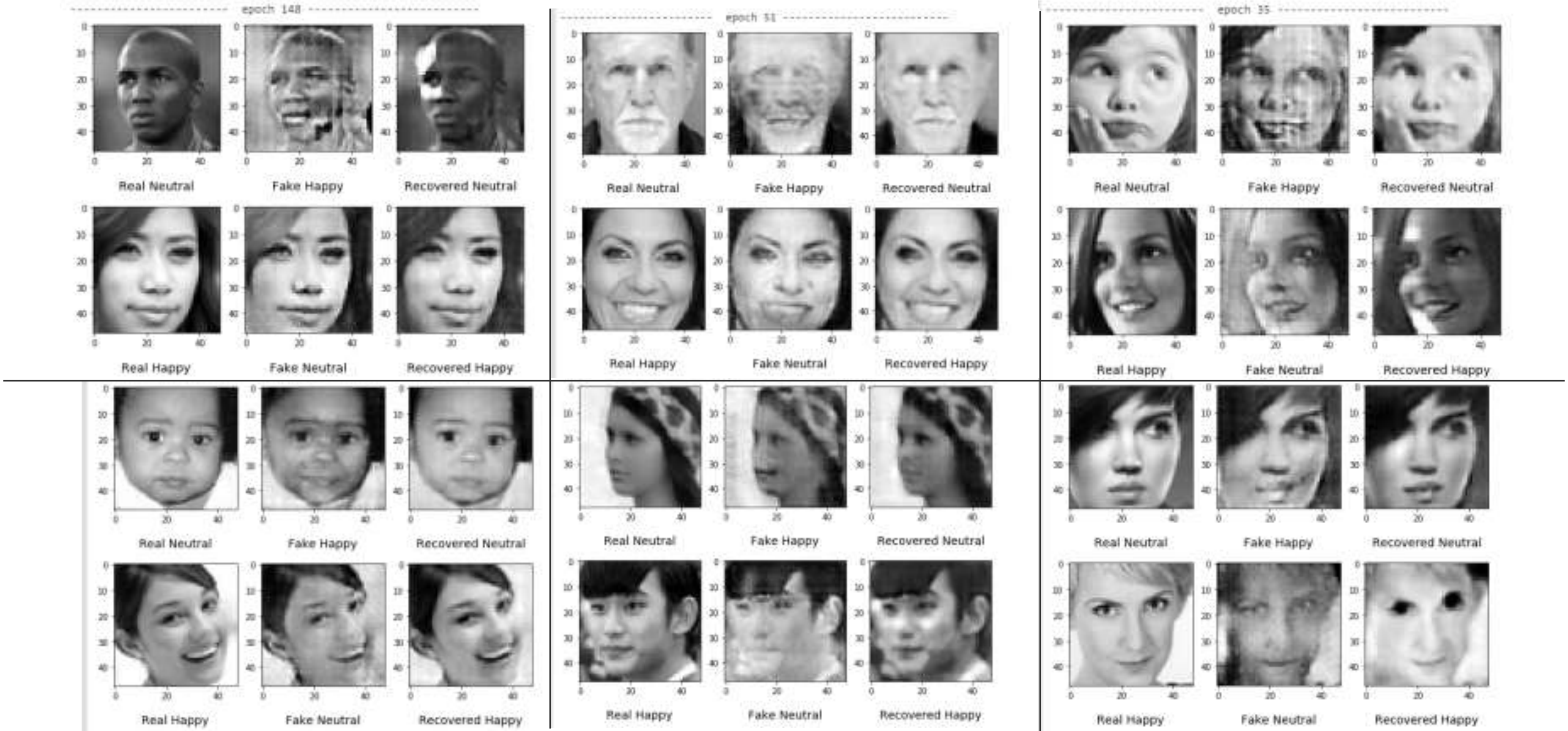
The Discriminator - a simple CNN network, that determinates if the image is fake or real.




Discriminator Network

# First results

- Neutral -> Happy transition



# Problems

- “Dirty” dataset, unbalanced classes, mislabeled data
- Similarity between classes (for example: fear-angry, sad-neutral)
- Lack of data (Disgust Class – 550 images)
- Discriminator learns faster than the Generator.
- Vanishing gradient
- Quality and artifacts of output images

# **Solution –** *Weighted Cycle Loss*

- Data augmentation, transform on training
- Different learning rates for generator and discriminator: 0.0002, 0.0001
- Learning rate decay
- Soft labels for discriminator: Real target is 0.9 instead of 1
- Improving quality by changing cycle loss to:

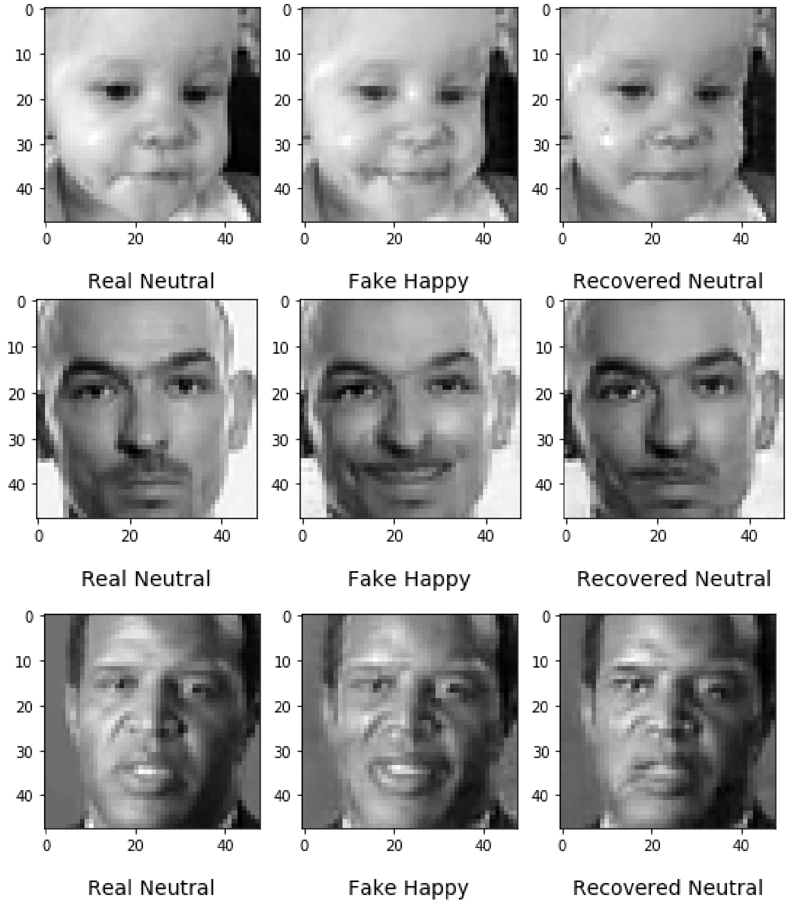
$$\mathcal{L}_{cyc}(G,F,D_A,A,\gamma) = \mathbb{E}_{a\sim p_{data}(a)}\left[D_A(a)\cdot\left[\gamma\cdot\left\|f_{D_A}\left(F\big(G(a)\big)\right) - f_{D_A}(a)\right\|_1 + (1-\gamma)\cdot\left\|F\big(G(a)\big) - a\right\|_1\right]\right]$$

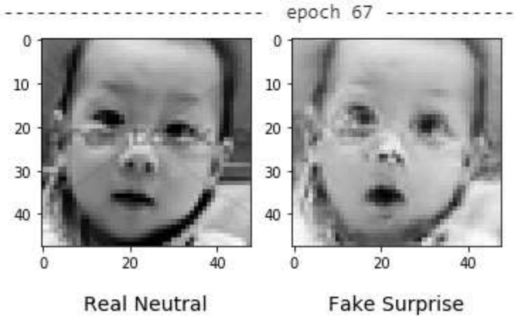
Where: $\gamma \in [0,1]$ – linearly increase with epochs, to 1, $f_{D_{(\cdot)}}$ - is the future extractor using last layer of $D_{(\cdot)}$

- So final objective updated to:

$$\mathcal{L}(G,F,D_A,D_B) = \mathcal{L}_{GAN}(G,D_B,A,B) + \mathcal{L}_{GAN}(F,D_A,A,B) + \lambda\mathcal{L}_{cyc}(G,F,D_A,A,\gamma) + \lambda\mathcal{L}_{cyc}(G,F,D_B,B,\gamma)$$

# Results of improved model




# The Conclusion

So as we saw, we have a lot of problems, such as:

- model instability;
- vanishing gradient;
- dirty or small dataset;
- control over the training;
- battle between generator and discriminator etc.

# The *Wasserstein* Cycle GAN Model

So how can we improve stability of training? The answer is - The Wasserstein distance.

Wasserstein CycleGAN - is a two-way Wasserstein GAN, that consists of 2 *Critics* and 2 *Generators*.

The idea is, for distribution of mass $\mu(x)$ on a space $X$, we wish to transport the mass in such a way that it is transformed into the distribution $\nu(x)$ on the *same* space.

# Theory Background - *The Wasserstein distance*

Our main goal and bottle-neck is to create data, that has same distribution as targeted domain, one of the most suitable and available methods for this task is *The Wasserstein distance.*

*The Wasserstein distance* is the minimum cost of transporting mass in converting the data distribution $\boldsymbol{q}$ to the data distribution $\boldsymbol{p}$. The Wasserstein distance for the real data distribution $\boldsymbol{Pr}$ and the generated data distribution $\boldsymbol{Pg}$ is mathematically defined as the greatest lower bound (infimum) for any transport plan.

# **Theory Background -** *The Wasserstein distance*

- The Wasserstein distance loss:

$$W(\mathbb{P}_r, \mathbb{P}_g) = \inf_{\gamma \in \Pi(\mathbb{P}_r, \mathbb{P}_g)} \mathbb{E}_{(x,y)\sim\gamma}[\|x - y\|]$$

Where $\Pi(\mathbb{P}_r, \mathbb{P}_g)$ – denotes the set of all joint distributions $\gamma(x, y)$, whose marginals are respectively $Pr$ and $Pg$.

- However, the equation for the Wasserstein distance is highly intractable. Using the *Kantorovich-Rubinstein duality*, we can simplify the calculation to:

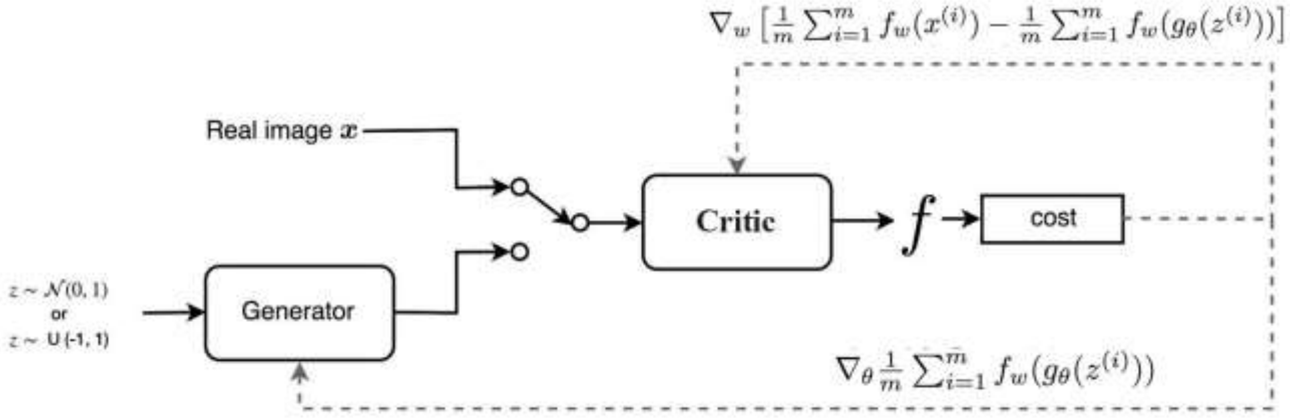
$$W(\mathbb{P}_r, \mathbb{P}_\theta) = \sup_{\|f\|_L \leq 1} \mathbb{E}_{x\sim\mathbb{P}_r}[f(x)] - \mathbb{E}_{x\sim\mathbb{P}_\theta}[f(x)]$$

Where $sup$ is the least upper bound and $f$ is a $1 - Lipschitz\ function$ following this constraint:

$$|f(x_1) - f(x_2)| \leq 1 \cdot |x_1 - x_2|$$

# **Theory Background -** *The Wasserstein distance*

So to calculate *the Wasserstein distance*, we just need to find a *1-Lipschitz function*. We build a deep network to learn it. This network is very similar to the discriminator $\boldsymbol{D}$, just without the sigmoid function and outputs a scalar score* rather than a probability.

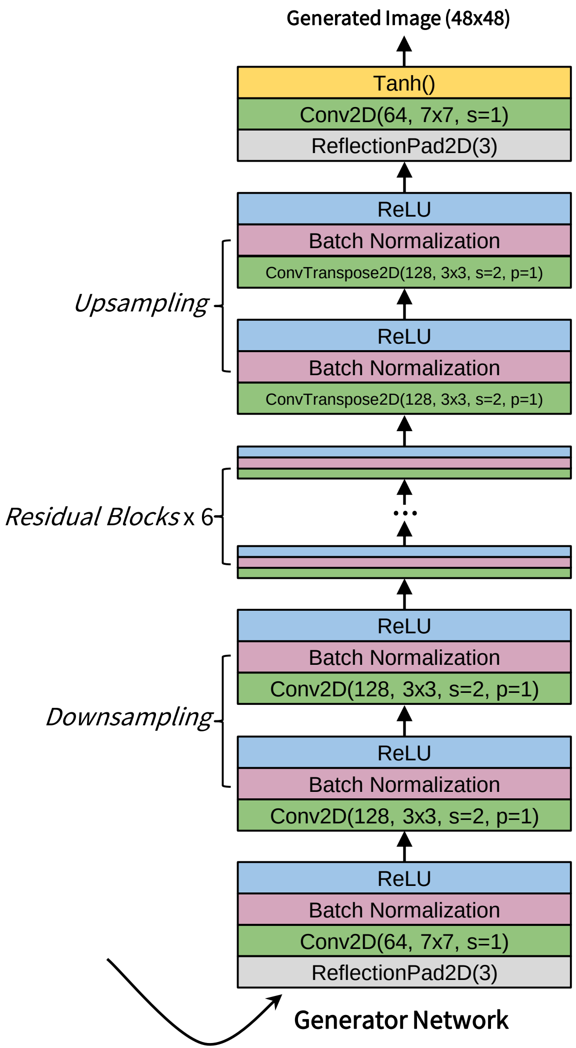



* - This score can be interpreted as how real the input images are.

# The Networks: *Generator*

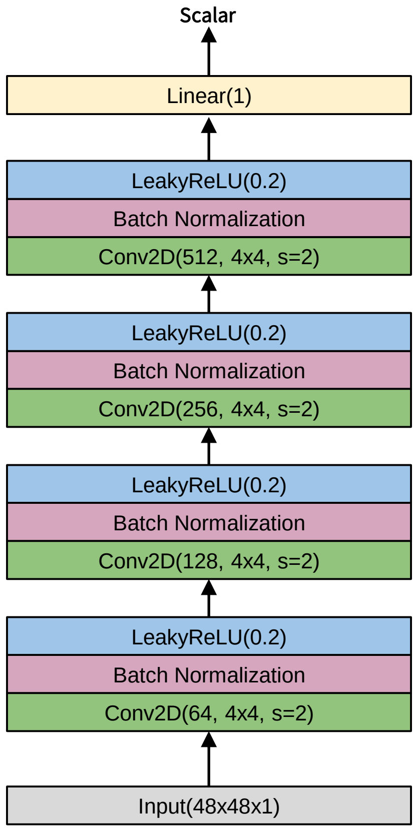
The Generator same as in Cycle GAN:

- Decode (downsampling)
- Transferring (6 residual blocks)
- Encode (upsampling).



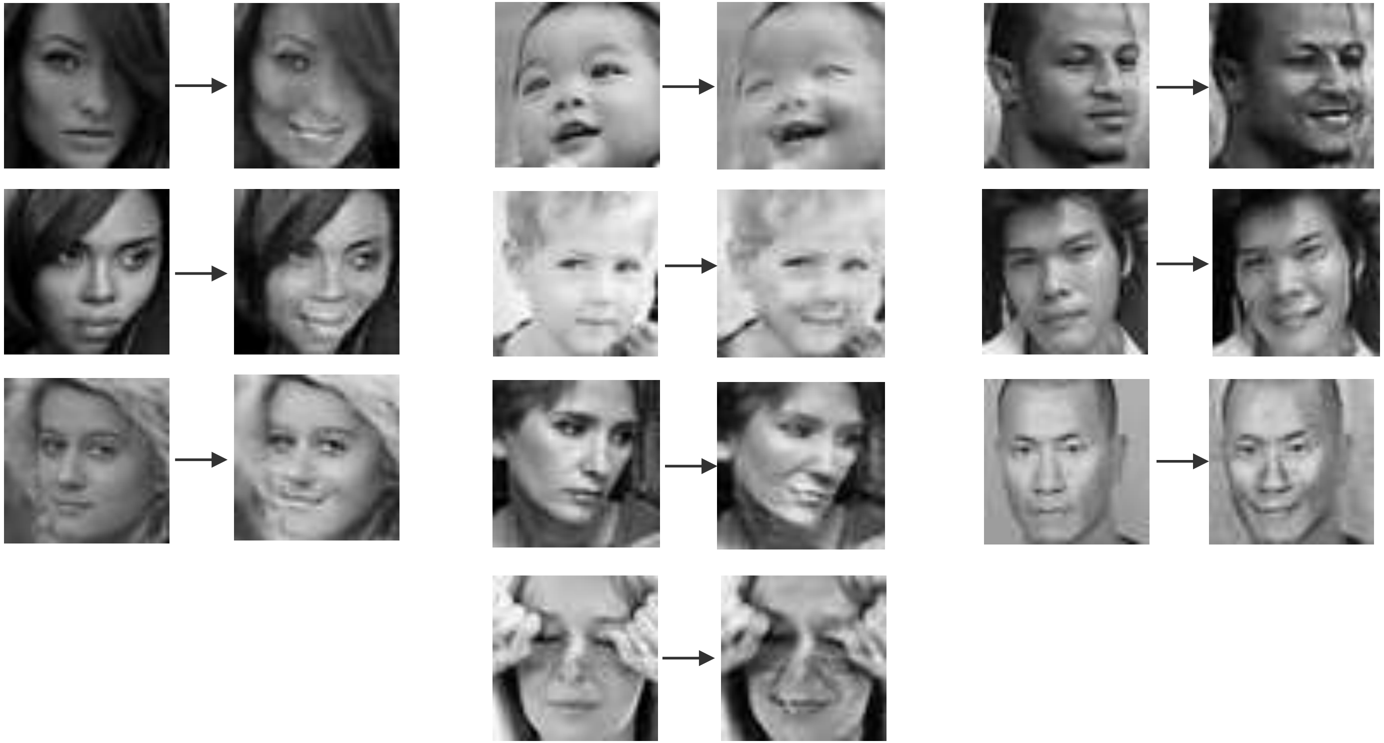
# The Networks: *Critic*

Same as Discriminator, but without Sigmoid activation at the end.




Critic Network

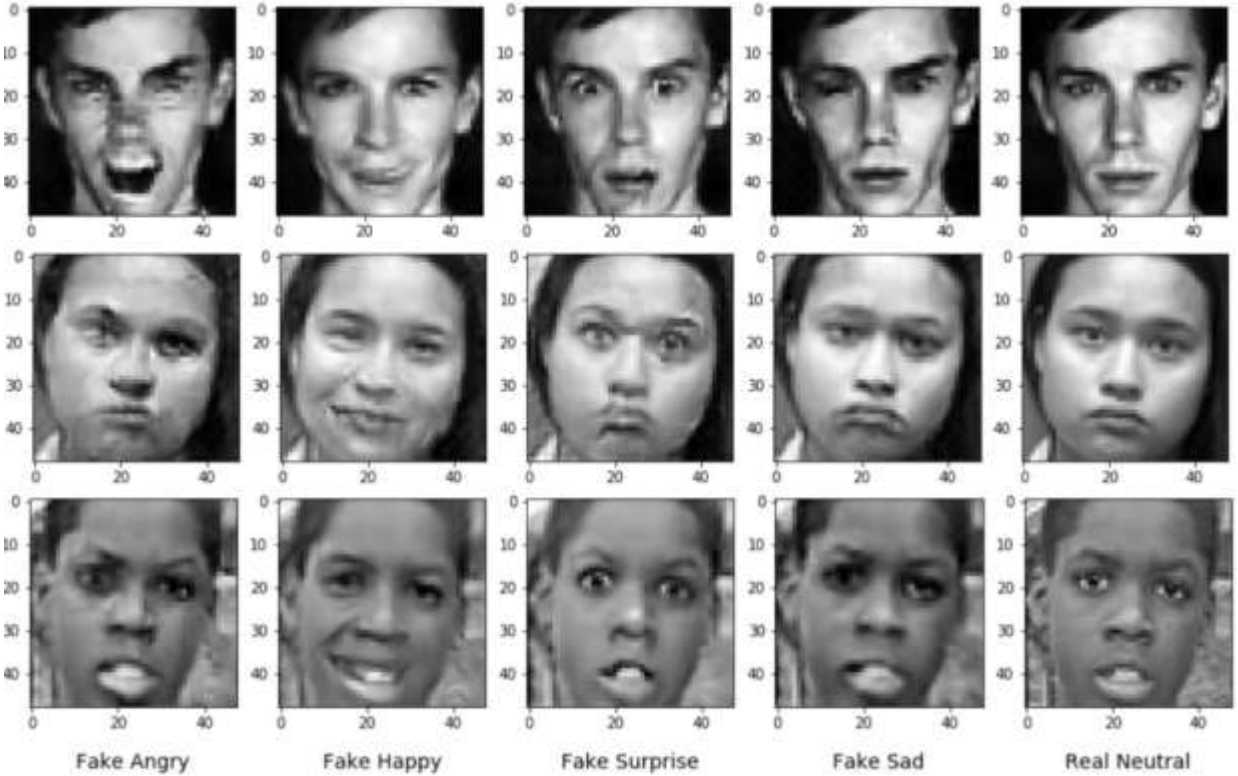
# Results of Wasserstein Cycle Gan



# The Results

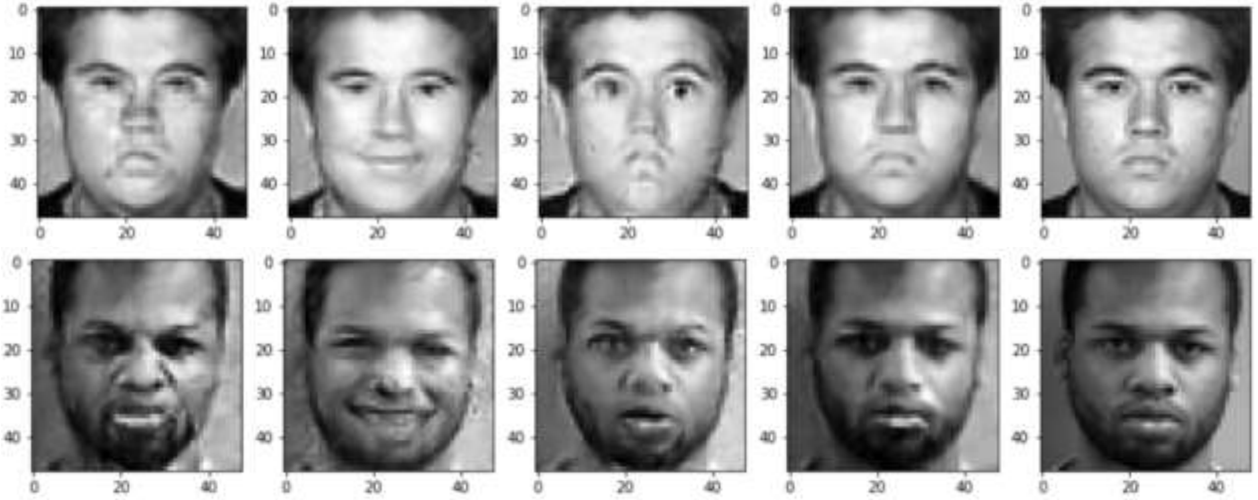
Let`s see visual results of the work.

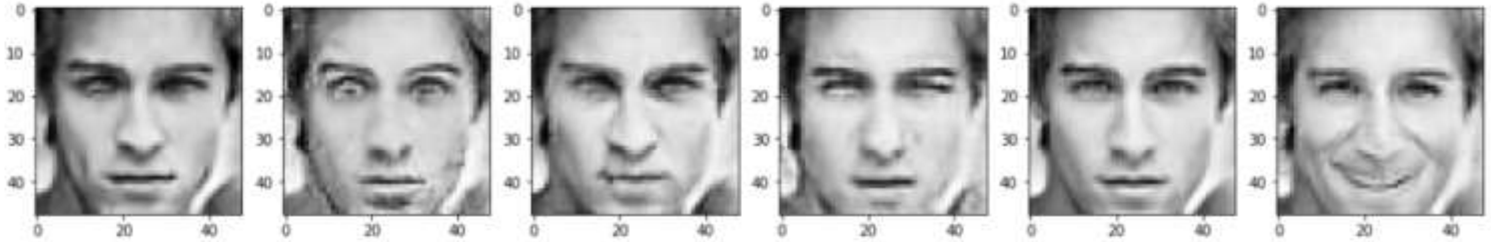
# Other results : Teenager



# Other results: Women

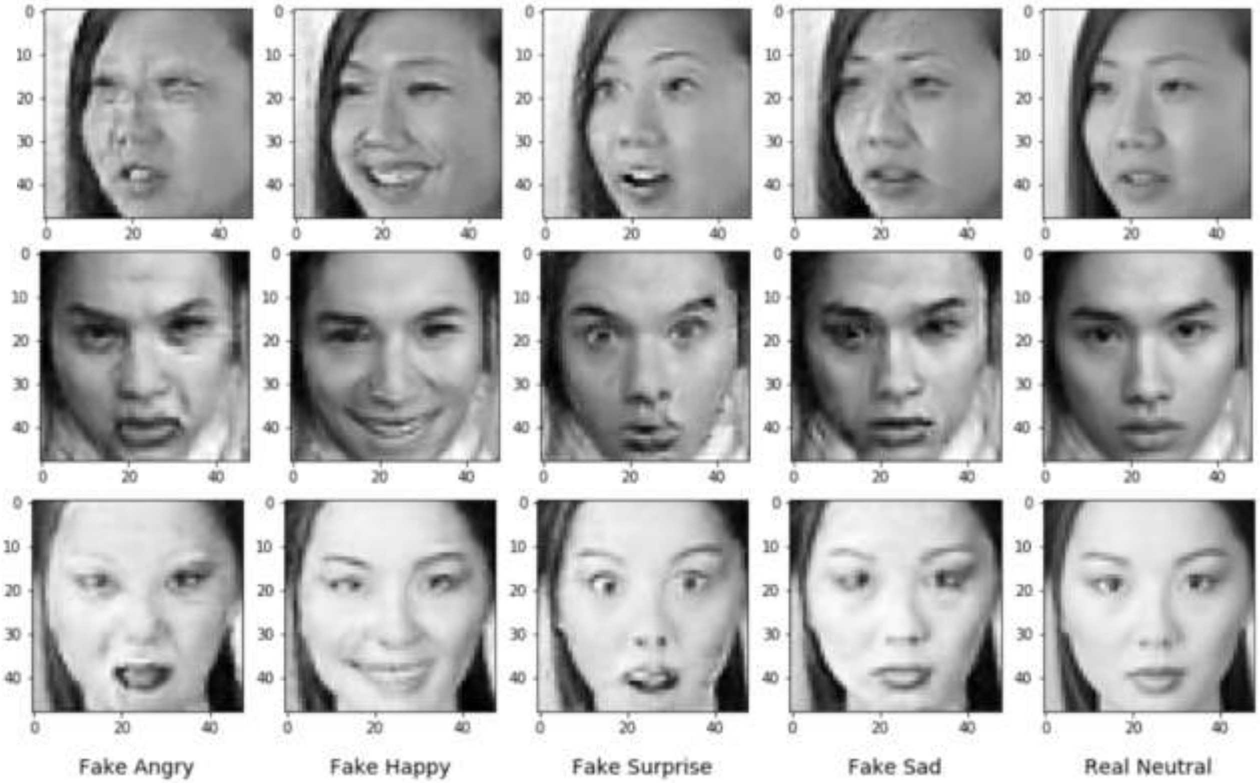
# Other results: Men



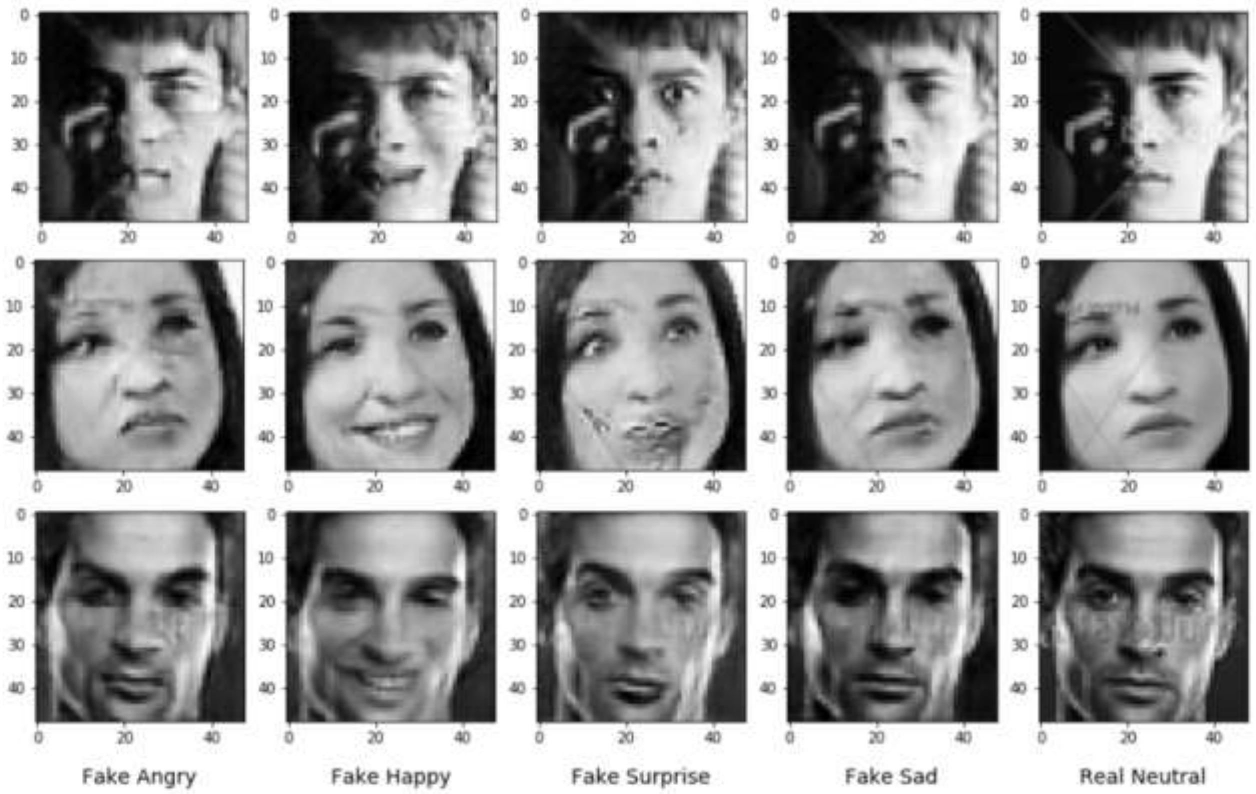
# Other results: Old

# Other results: Asian

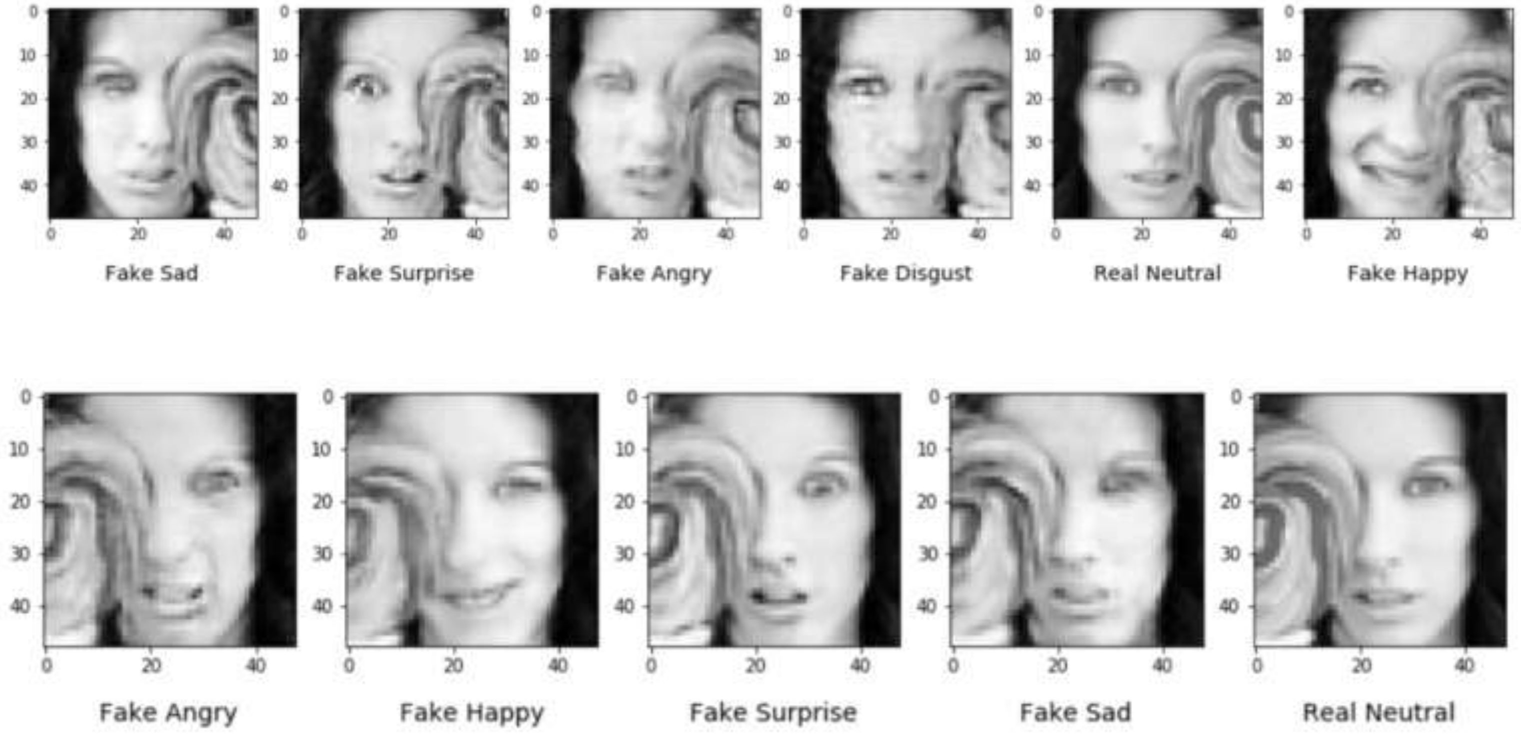


# Other results: Noisy

# Other results: Noisy - Watermarks

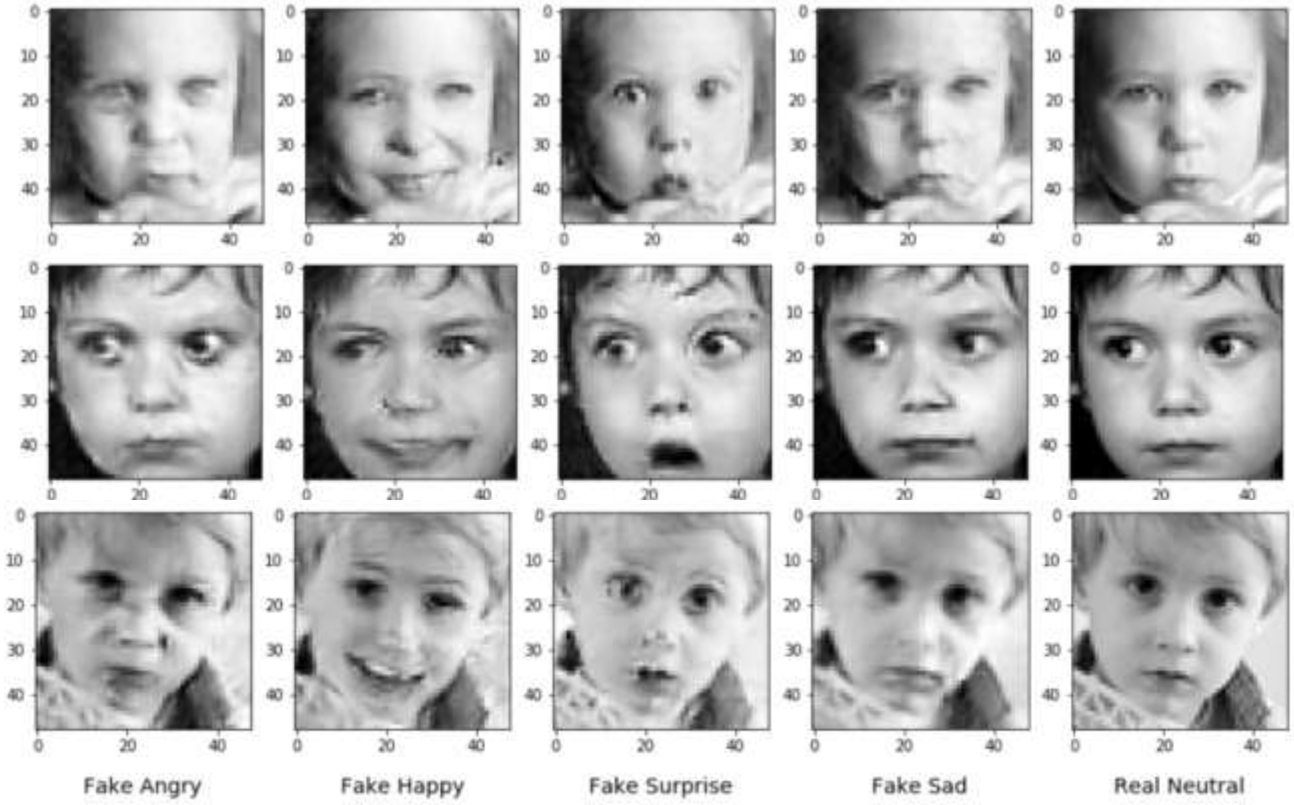


# Results on transformed data



# Other results: Children #1

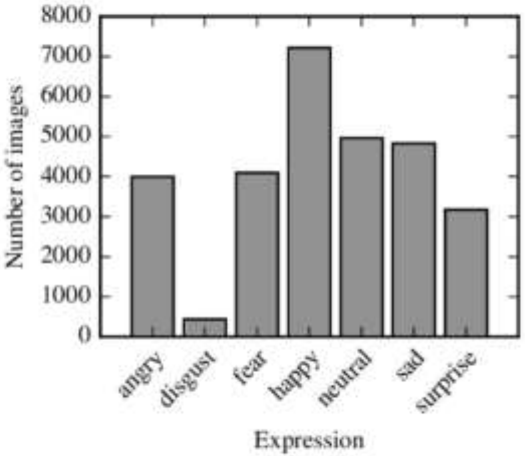
# Other results: Children #2



# Part B

- Classifiers on FER2013 Dataset
- Fake Neutral Images Generator Using DCGAN

# The Classifier




FER2013

Classification task on “dirt” dataset , maybe challenging.

Results were checked on two different classifiers:

- Simple (~65%)
- Current State of the art (73%)

# Surreal (Paper) Classifier - Architecture

| Layer Type | Configuration |
| --- | --- |
| Input image | 48*48*1 |
| Convolution&ReLU | [3, 3, 1, 64] s=1 |
| Max-Pooling&Norm | [1, 3, 3, 1] s=2 |
| Convolution&ReLU | [3, 3, 64, 128] s=1 |
| Max-Pooling&Norm | [1, 3, 3, 1] s=2 |
| FC*2 | 256 |
| Softmax | [256, 7] |
| Output logits | [7] |

# Surreal (Paper) Classifier - Architecture

Doesn`t work

| Layer Type | Configuration |
|---|---|
| Input image | 48*48*1 |
| Convolution&ReLU | [3, 3, 1, 64] s=1 |
| Max-Pooling&Norm | [1, 3, 3, 1] s=2 |
| Convolution&ReLU | [3, 3, 64, 128] s=1 |
| Max-Pooling&Norm | [1, 3, 3, 1] s=2 |
| FC*2 | 256 |
| Softmax | [256, 7] |
| Output logits | [7] |

# Simple Classifier - Architecture

```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 46, 46, 64)        640
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 46, 46, 64)        36928
_________________________________________________________________
batch_normalization_1 (Batch (None, 46, 46, 64)        256
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 23, 23, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 23, 23, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 23, 23, 128)       73856
_________________________________________________________________
batch_normalization_2 (Batch (None, 23, 23, 128)       512
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 23, 23, 128)       147584
_________________________________________________________________
batch_normalization_3 (Batch (None, 23, 23, 128)       512
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 11, 11, 128)       0
_________________________________________________________________
dropout_2 (Dropout)          (None, 11, 11, 128)       0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 11, 11, 256)       295168
_________________________________________________________________
batch_normalization_4 (Batch (None, 11, 11, 256)       1024
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 11, 11, 256)       590080
_________________________________________________________________
batch_normalization_5 (Batch (None, 11, 11, 256)       1024
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 5, 5, 256)         0
_________________________________________________________________
dropout_3 (Dropout)          (None, 5, 5, 256)         0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 5, 5, 512)         1180160
_________________________________________________________________
batch_normalization_6 (Batch (None, 5, 5, 512)         2048
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 5, 5, 512)         2359808
_________________________________________________________________
batch_normalization_7 (Batch (None, 5, 5, 512)         2048
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 2, 2, 512)         0
_________________________________________________________________
dropout_4 (Dropout)          (None, 2, 2, 512)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 2048)              0
_________________________________________________________________
dense_1 (Dense)              (None, 512)               1049088
_________________________________________________________________
dropout_5 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_2 (Dense)              (None, 256)               131328
_________________________________________________________________
dropout_6 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_3 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_7 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_4 (Dense)              (None, 7)                 903
=================================================================
Total params: 5,905,863
Trainable params: 5,902,151
Non-trainable params: 3,712
_________________________________________________________________
```

# Simple Classifier - Results

Baseline:

```
Accuracy of the network on the 3589 test images: 65.09 %

Accuracy of Angry : 53 % of 262 / 491 total
Accuracy of Disgust : 60 % of 33 / 55 total
Accuracy of  Fear : 46 % of 244 / 528 total
Accuracy of Happy : 85 % of 750 / 879 total
Accuracy of   Sad : 44 % of 262 / 594 total
Accuracy of Surprise : 78 % of 327 / 416 total
Accuracy of Neutral : 73 % of 458 / 626 total
```

Baseline + Synthetic Data:

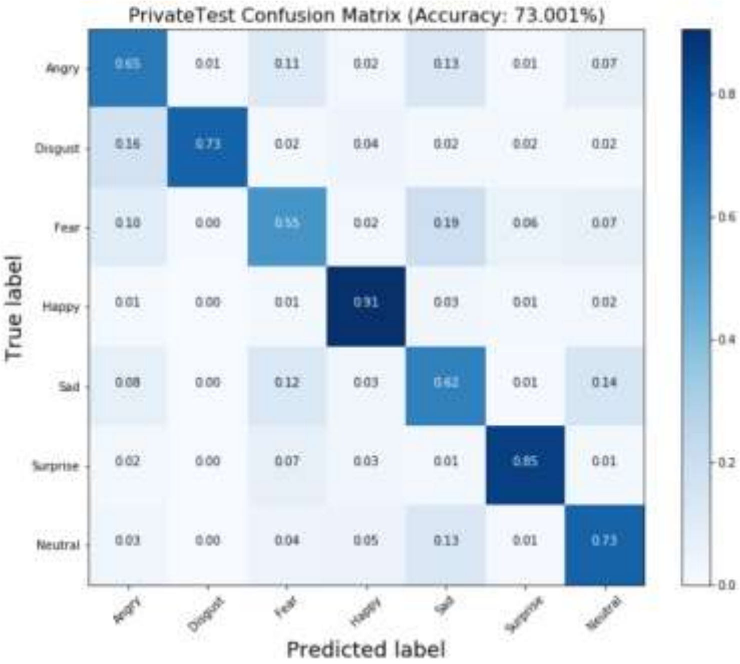
```
Accuracy of the network on the 3589 test images: 66.26 %

Accuracy of Angry : 57 % of 282 / 491 total      +4%
Accuracy of Disgust : 65 % of 36 / 55 total      +5%
Accuracy of  Fear : 51 % of 271 / 528 total      +5%
Accuracy of Happy : 87 % of 767 / 879 total      +2%
Accuracy of   Sad : 45 % of 271 / 594 total      +1%
Accuracy of Surprise : 78 % of 328 / 416 total ~0%
Accuracy of Neutral : 67 % of 423 / 626 total  -6%(*)
```

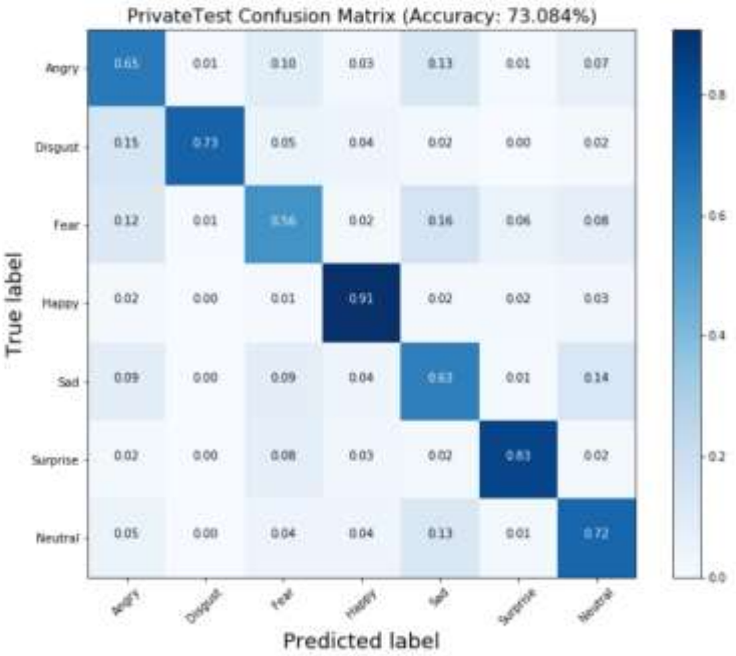
*- As you can see, we diminish Neutral Class, so what can we do?
Generate Neutral Class, more in future works section.

# SOTA Classifier (*VGG19*) - Results

Baseline:




Baseline + Synthetic Data:




Can we achieve state of the art?!

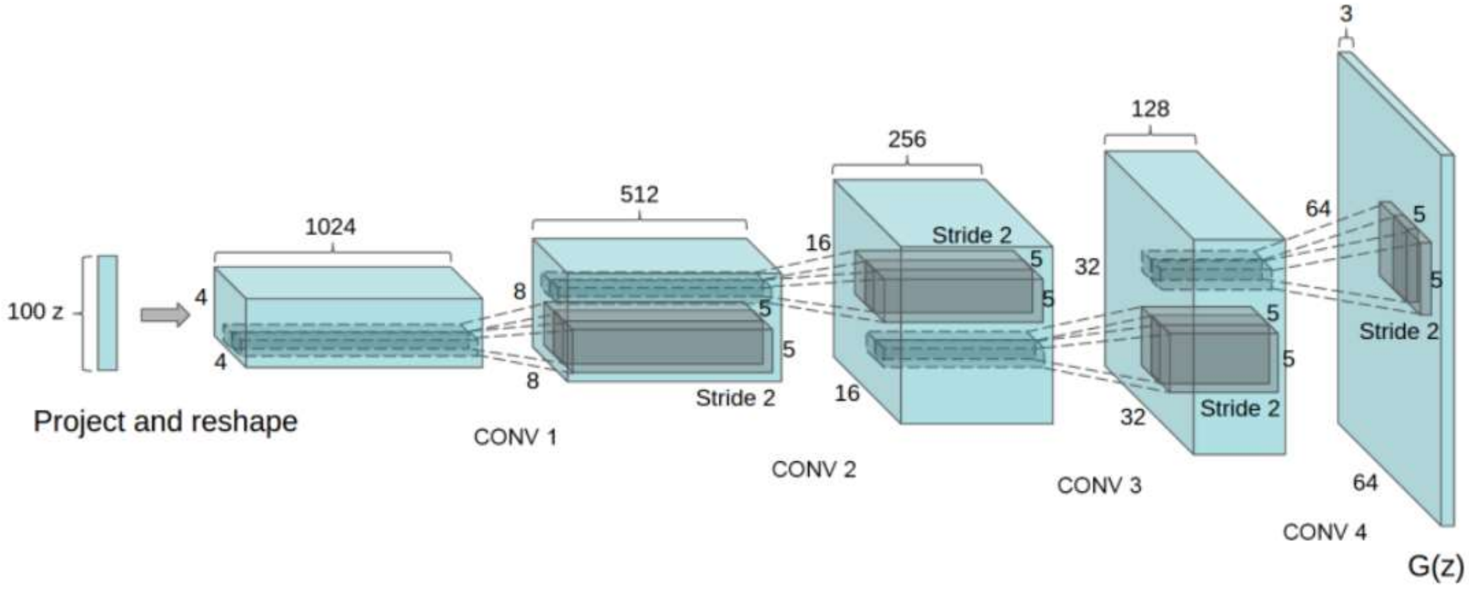
# The
# Fake GAN



So how can we supply more data, with the same distribution? The answer is, we will create it.

Fake GAN using DCGAN, WGAN-GP

# Generator - Architecture



# Discriminator - Architecture

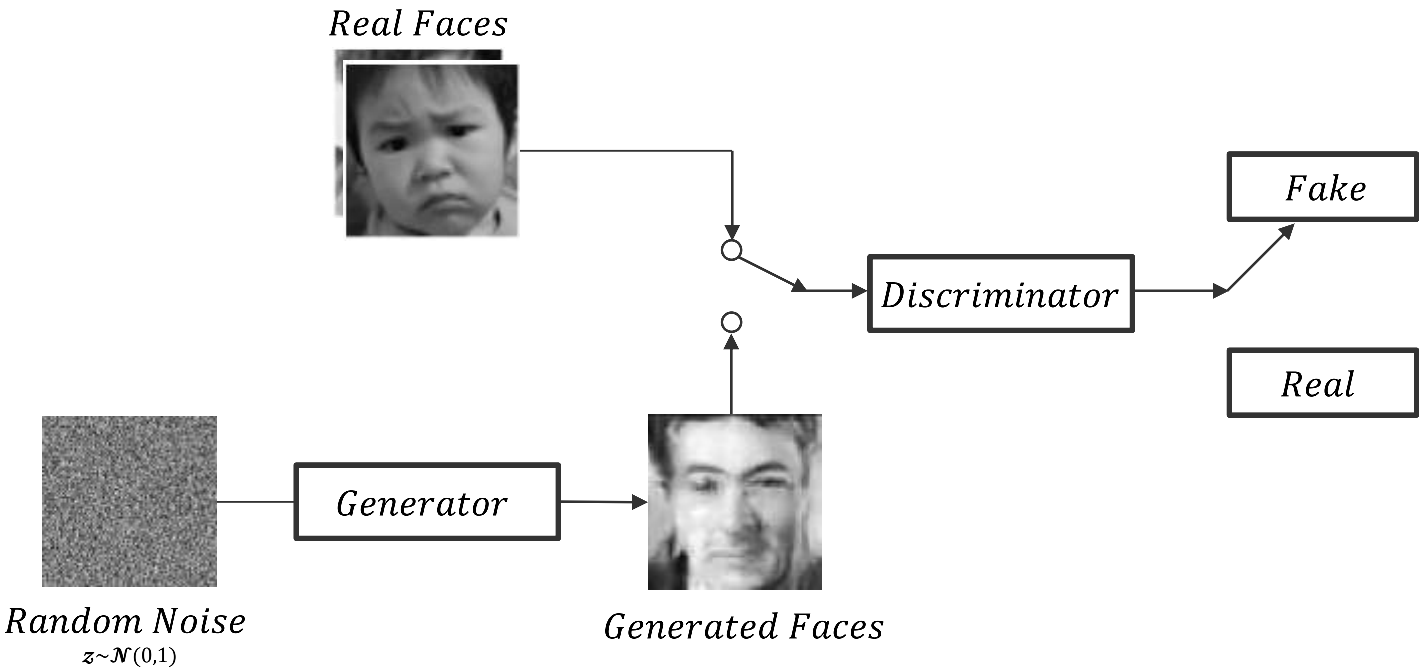
The generator, is designed to map the latent space vector ($Z$) to data-space.
Since data are images, converting $Z$ to data-space means ultimately creating an image with the same size as the training images (i.e. 1x48x48).
In practice, this is accomplished through a series of strided two dimensional convolutional transpose layers, each paired with a 2d batch norm layer and a ReLU activation.

# Discriminator - Architecture

Discriminator - is a binary classification network that takes an image as input and outputs a scalar probability that the input image is real (as opposed to fake).

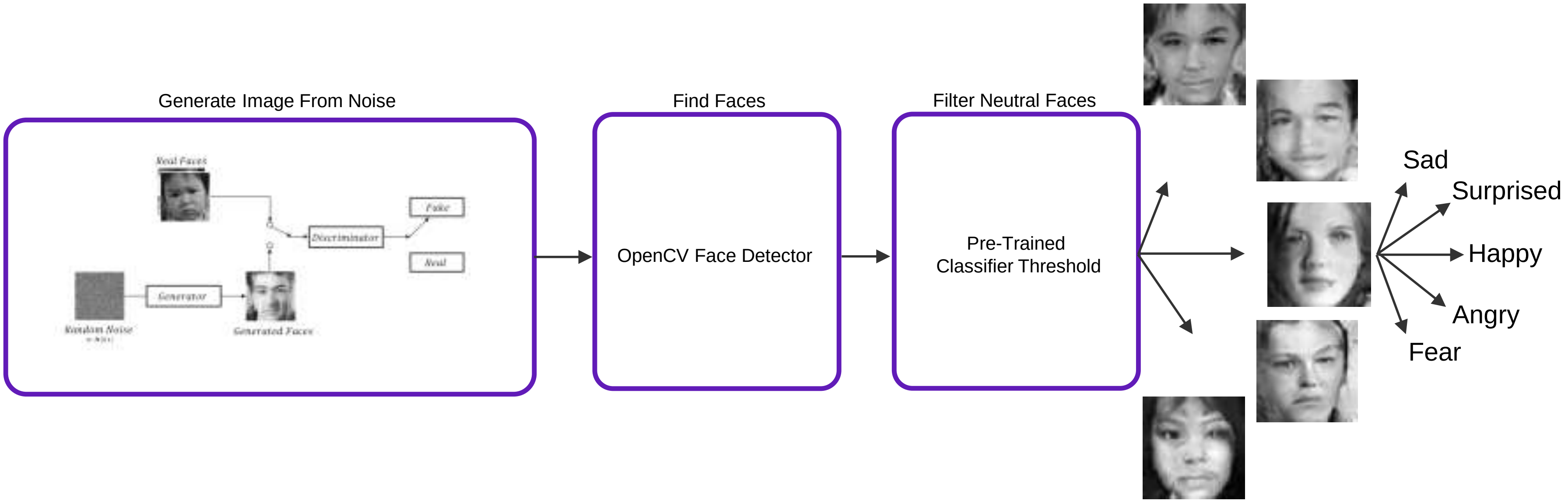
Discriminator takes a 1x48x48 input image, processes it through a series of Conv2d, BatchNorm2d, and LeakyReLU layers, and outputs the final probability through a Sigmoid activation function.

# Overview



Real Faces
Fake
Discriminator
Real
Generator
Random Noise
$z \sim \mathcal{N}(0,1)$
Generated Faces

# Overview



Generate Image From Noise
Real Faces
Discriminator
Fake
Real
Generator
Random Noise
Generated Faces
Find Faces
OpenCV Face Detector
Filter Neutral Faces
Pre-Trained
Classifier Threshold
Sad
Surprised
Happy
Angry
Fear

# Future work

- Further work with generated data:
    - Analyze distribution
    - Analyze similarity of generate and original images, by using ssim()
- Can we improve state of the art results
- Generation of Neutral Class for FER2013, using Fake GAN
- Improvement Fake GAN by using WGAN-GP
- Put all together:
    - Use Fake Gan as part of Cycle GAN architecture
    - Analyze difference between Cycle GAN, Improved Cycle Gan and Wasserstein GAN
- Testing performance on generated data while training on original and vice versa

# The END