Optimization for Artificial Intelligence

Image Generation with GA

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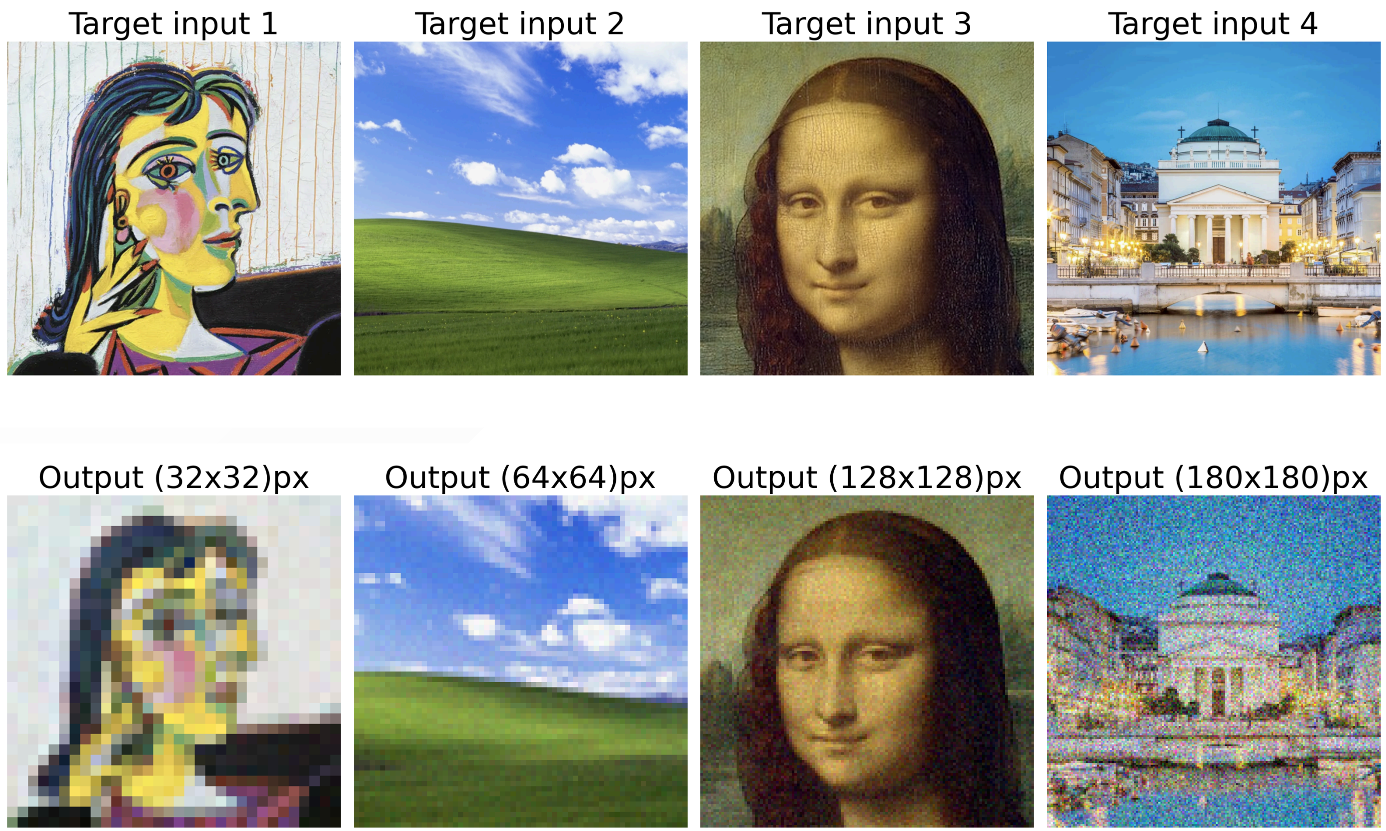
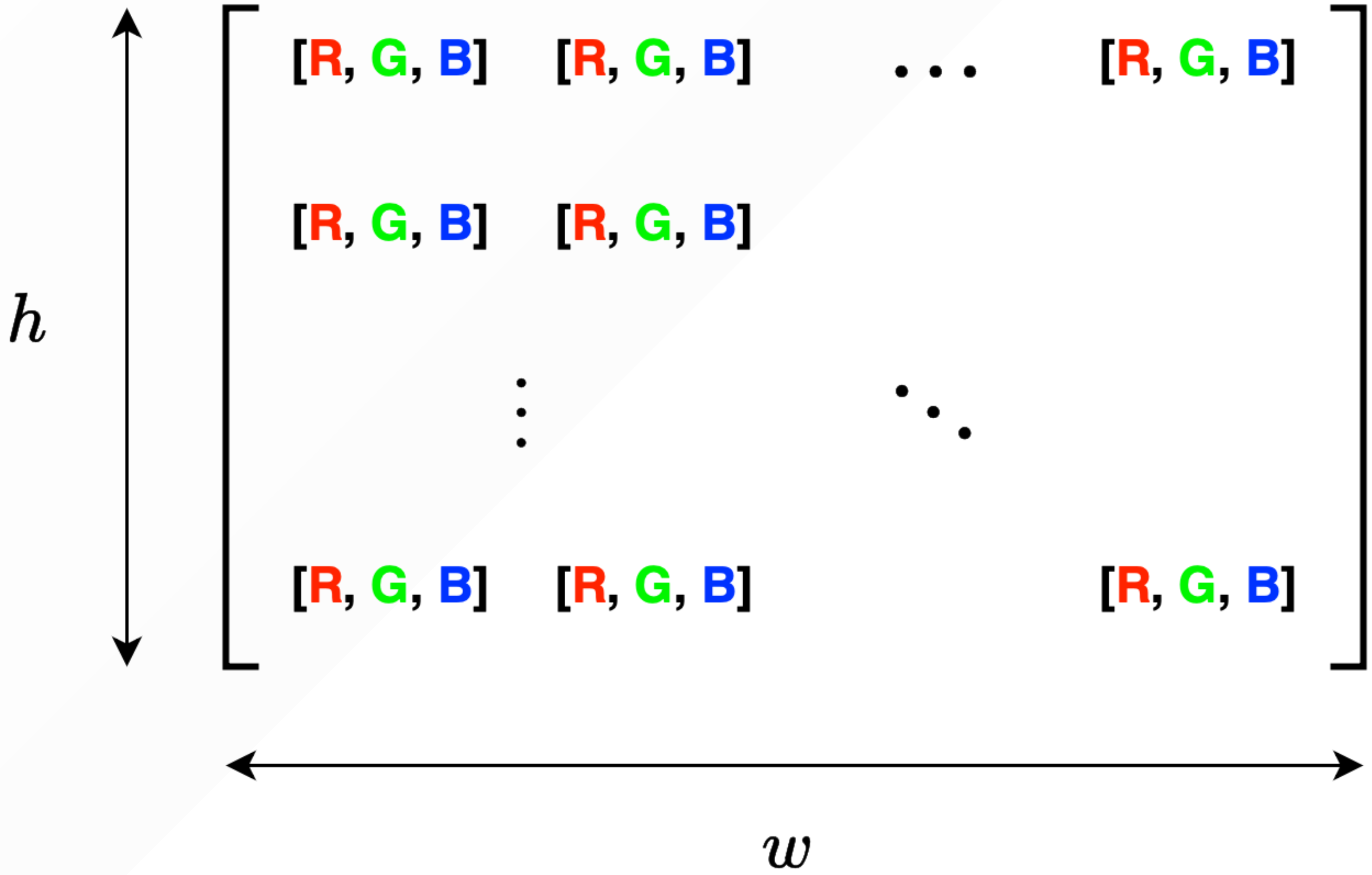
Problem statement

- Evolve a low resolution image to approximate a target image of higher resolution.
- **Input:** An image I which resolution is $R = (h \times w)$
- **Output:** An image I' which resolution is $R' = (h' \times w')$ with $h' \ll h$, $w' \ll w$



Individuals: RGB images

$(h \times w \times 3)$ tensor of 8-bit-integers



Preprocessing

- Resizing and normalizing target image

```python
from PIL import Image

def load_image(image_path: str, target_resolution: tuple) -> np.ndarray:
    img = Image.open(image_path).convert("RGB")
    img = img.resize(target_resolution, Image.Resampling.LANCZOS)
    return np.array(img)
```

Fitness function: MSE vs ΔE_{ab}

MSE fitness

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

- Easy to compute
- Compatible with RGB space $[0, 255]^3$
- May not be aligned with visual perception differences
- Bounded in $[0, 65025]$

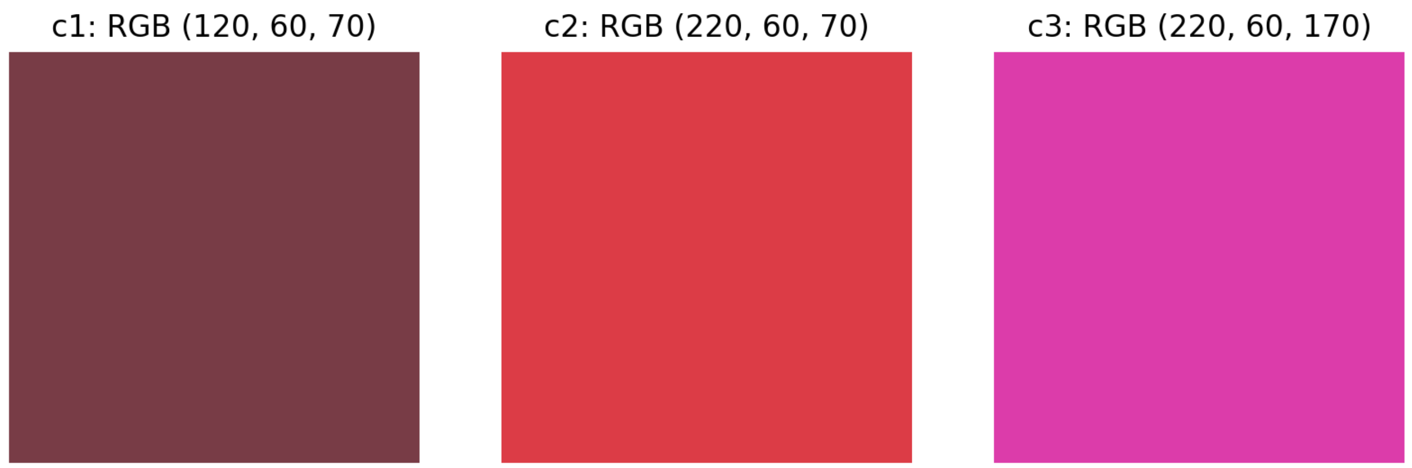
ΔE_{ab} fitness

- CIE-Lab colorspace is a 3D color space defined by the International Commission on Illumination (abbreviated CIE) in 1976.
- The three axes are:
  - L - perceptual lightness ax, a - red/green color ax, b - blue/yellow color ax

$$\Delta E_{ab} = \sqrt{(L_2 - L_1)^2 + (a_2 - a_1)^2 + (b_2 - b_1)^2}$$

- Demanding computation requiring conversion from RGB-space to CIE-Lab space
- Aligned with visual perception differences
- Bounded in $[0, 100]$

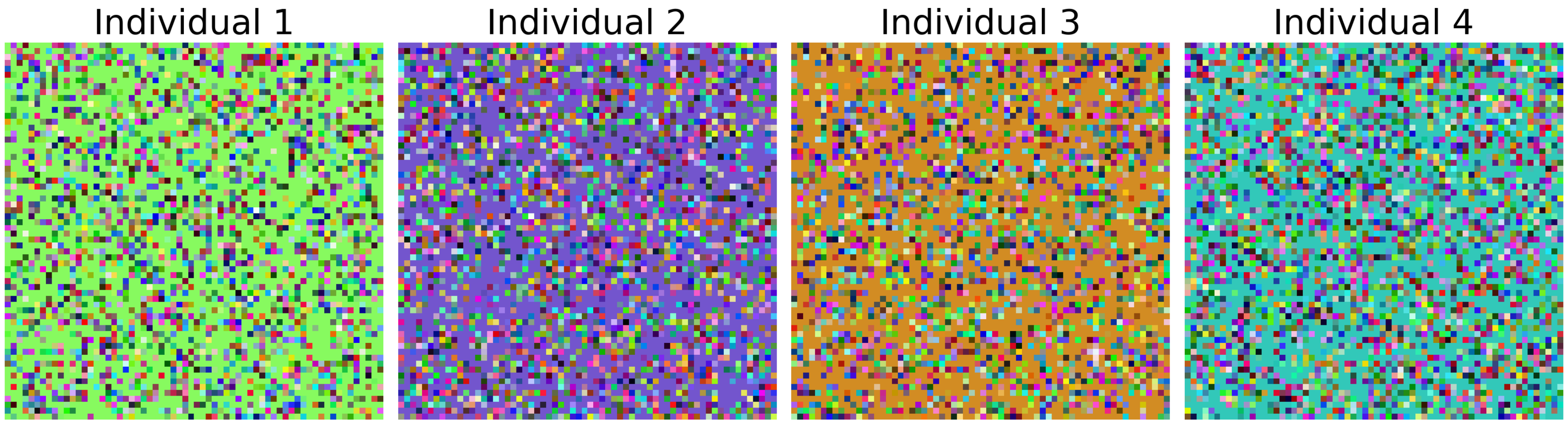
Differences in fitness



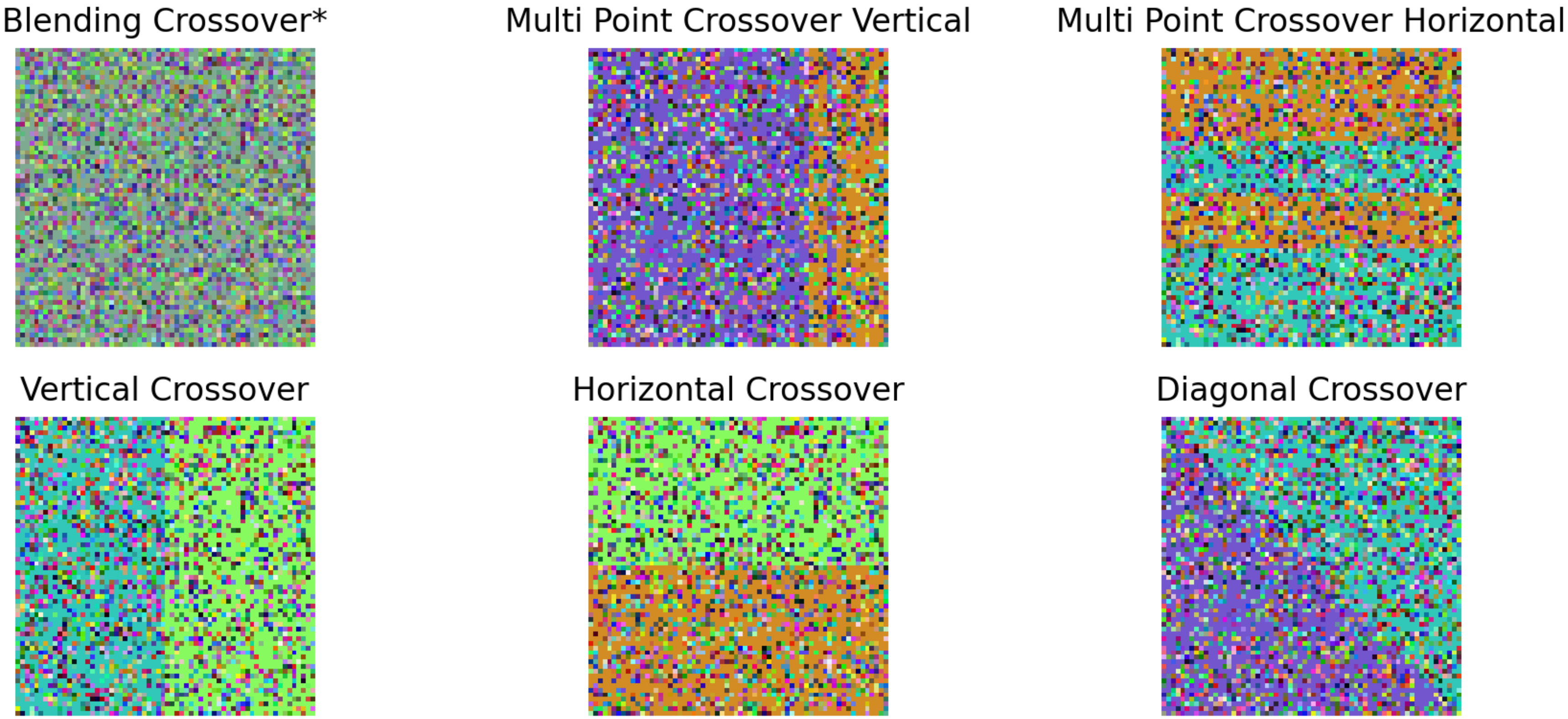
	Normalized MSE	Normalized ΔE_{ab}
c_1 vs c_2	0.05	0.47
c_2 vs c_3	0.05	0.57
c_1 vs c_3	0.10	0.56

Initial population generation

- Each individual is composed of randomly chosen pixel colors on a colored background
- Square images with $(n \times n)$ resolution for simplicity



Crossover



$$^{*}\mathrm{Blend}(I_A, I_B) = \alpha I_A + (1-\alpha) I_B, \quad \alpha = \mathrm{rd}(0,1)$$

Mutation

- Single point random mutation on pixel i within the range $v_i \pm 30$ on all RGB channels with a decreasing mutation rate
- Mutation rate exponential decrease law:

$$\text{mutation rate}(t) = \text{mutation rate}(0) \cdot \exp(-\beta \cdot t)$$

- Anti-stagnation strategy and termination criterion

```
if len(fitness_scores)>5 and best_fitness < fitness_scores[-5]:
  no_improvement_count = 0  # Reset stagnation counter
  mutation_rate = update_mutation_rate(min_mutation_rate, rate = max_mutation_rate, decay=0.005, generation=generation)
else:
  no_improvement_count += 1

if no_improvement_count >= stagnation_limit:
  mutation_rate = min(mutation_rate * 1.2, max_mutation_rate)
  no_improvement_count = 0  # Reset stagnation counter
  stagnation_count += 1

if (generation+1) >= 5000 and stagnation_count >= exit_limit:
  print(f"Stagnation limit reached. Exiting evolution loop.")
  break
```

Selection

- Tournament parents selection before crossover
- Steady state strategy after crossover and mutation

```
indices = np.argsort(offspring_fitnesses)[:replacement]
best_offspring = [new_offspring[i] for i in indices]
best_of_fitnesses = [offspring_fitnesses[i] for i in indices]
worst_indices = np.argsort(fitnesses)[-replacement:]

        for i, idx in enumerate(worst_indices):
            population[idx] = best_offspring[i]
            fitnesses[idx] = best_of_fitnesses[i]
```

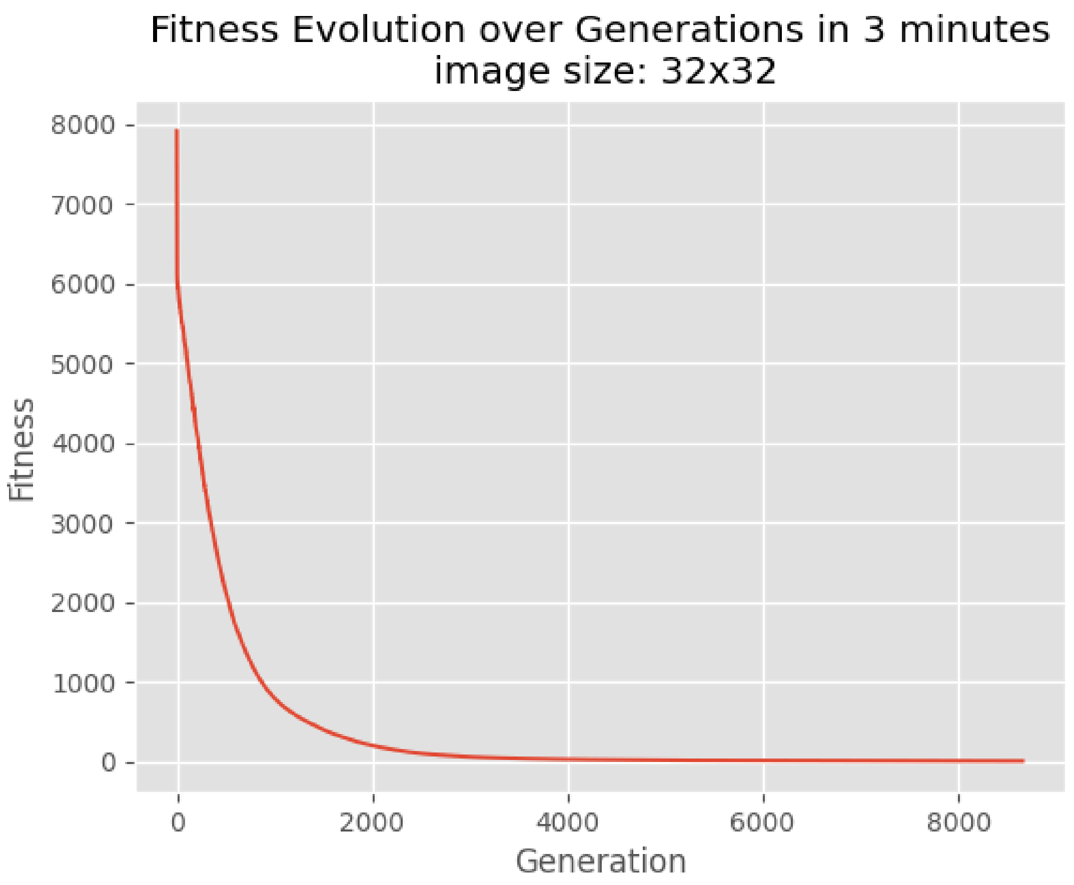
Experiments

- Problem scaled with respect to the output resolution to test the algorithm efficiency and effectiveness, using resolutions (in pixels) (32×32), (64×64), (128×128), (180×180)
- Tests with both MSE and ΔE_{ab} fitness functions
- Hyperparameters:
  - **population size**
  - **generations**: maximum number of generations
  - **mutation rate** (**mr**)
  - **tournament size**
  - **replacement**: individuals to replace at each iterations
  - **minimum** and **maximum mutation rate**
  - **stagnation limit**: limit of iterations without improvements before increasing **mr**
  - **exit limit**: limit of iterations without improvements before prematurely end the process

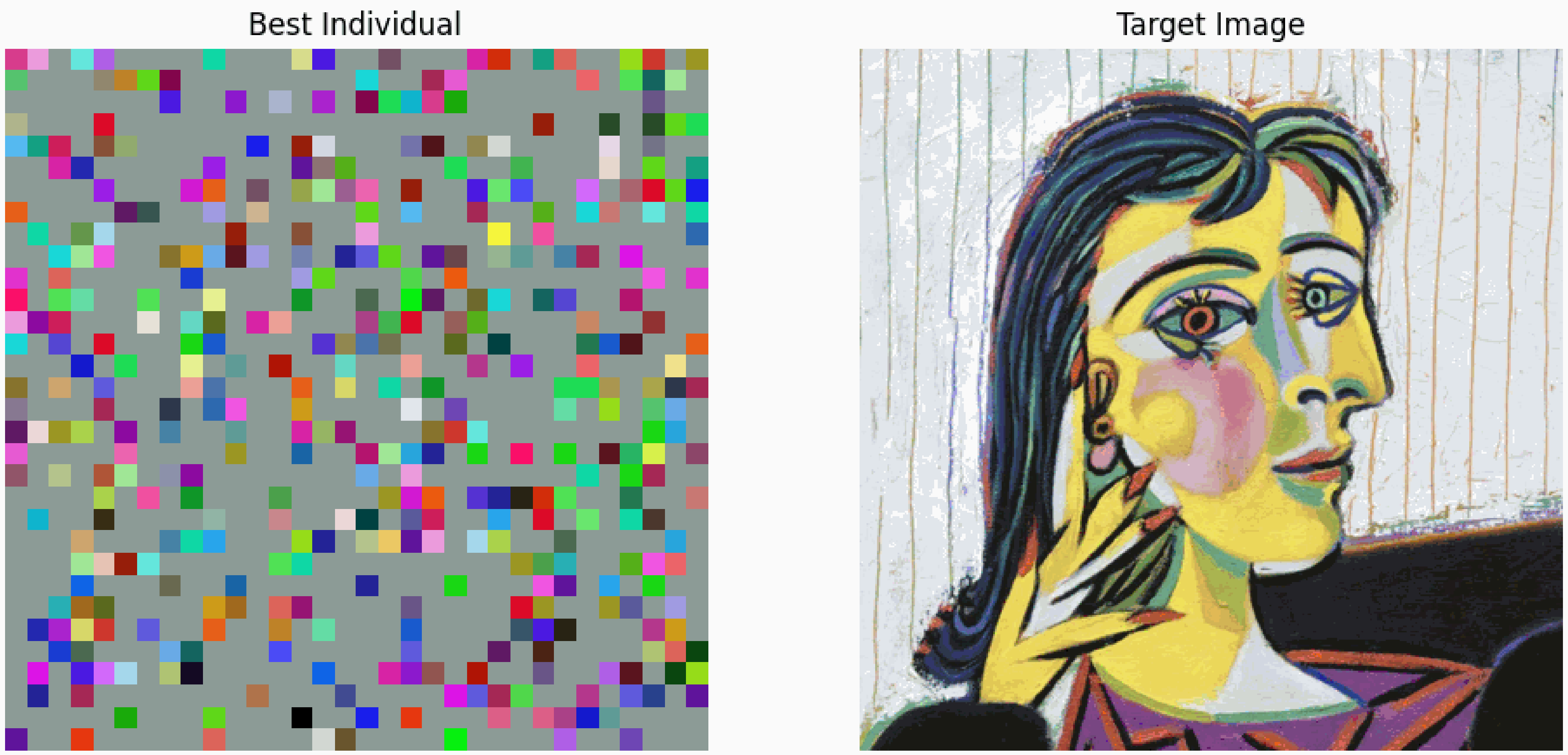
Results (MSE)

32x32px image

```
pop_size = 150, generations = 15000, mutation_rate = 0.2,
max_mutation_rate = 0.2, tournament_size = 8, replacement = 20,
min_mutation_rate = 0.0005, stagnation_limit = 10, n = 32, fit = 'mse')
```

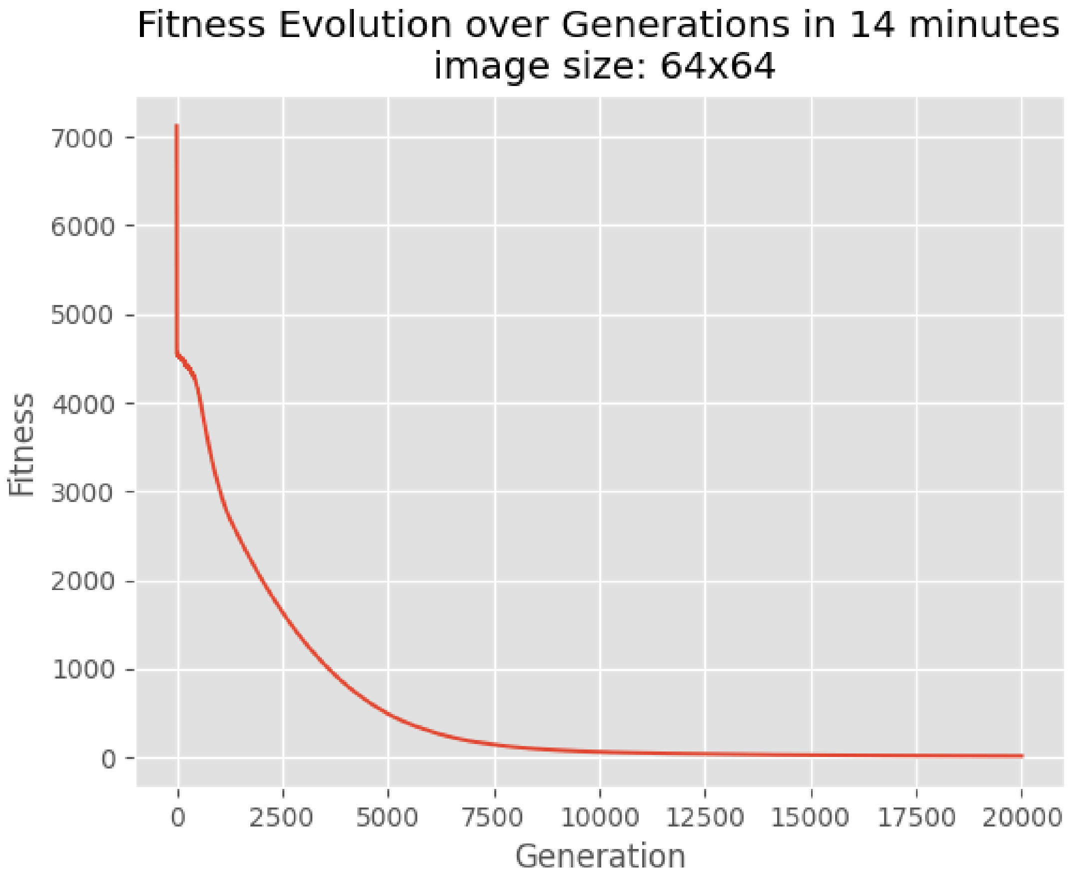


Resolution 32x32, Generation 1, Fitness = 7914.35



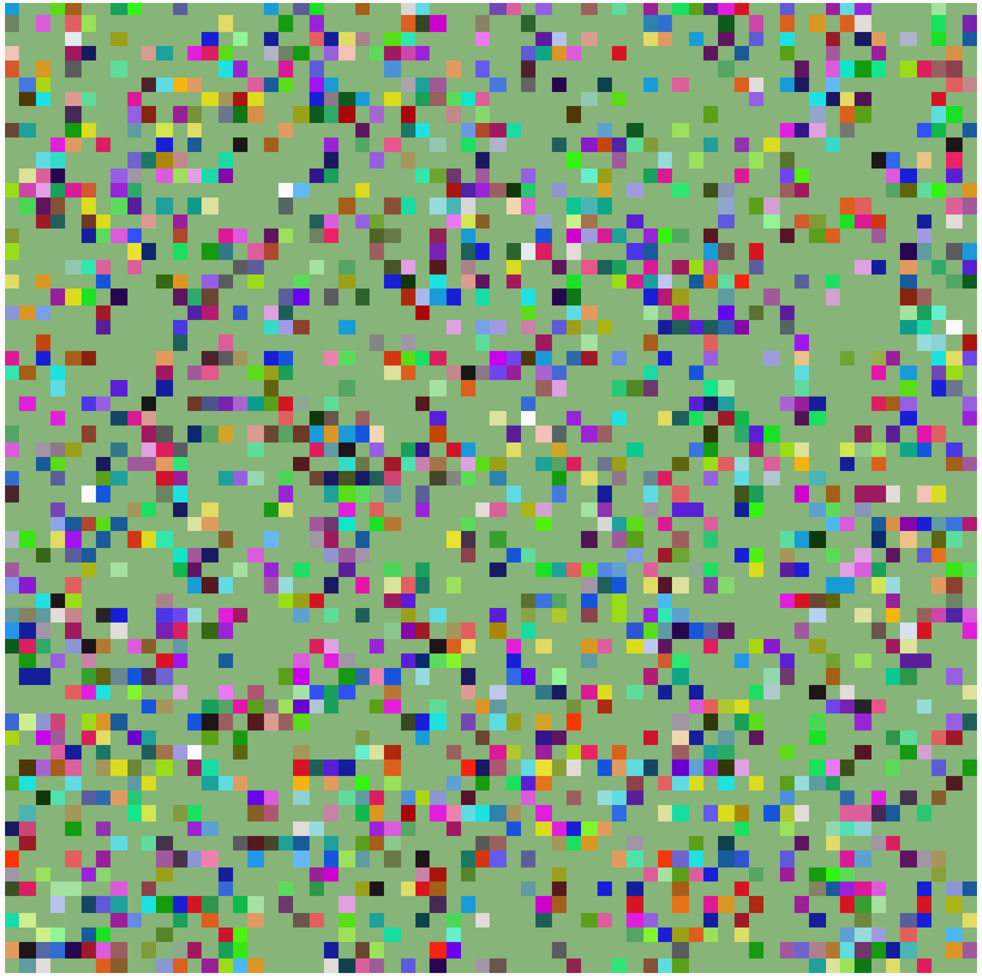
64x64px image

```
pop_size = 180, generations = 20000, mutation_rate = 0.35,
max_mutation_rate = 0.35, tournament_size = 10, replacement = 25,
min_mutation_rate = 0.0005, stagnation_limit = 20, n = 64, fit = 'mse')
```



Resolution 64x64, Generation 1, Fitness = 7119.75

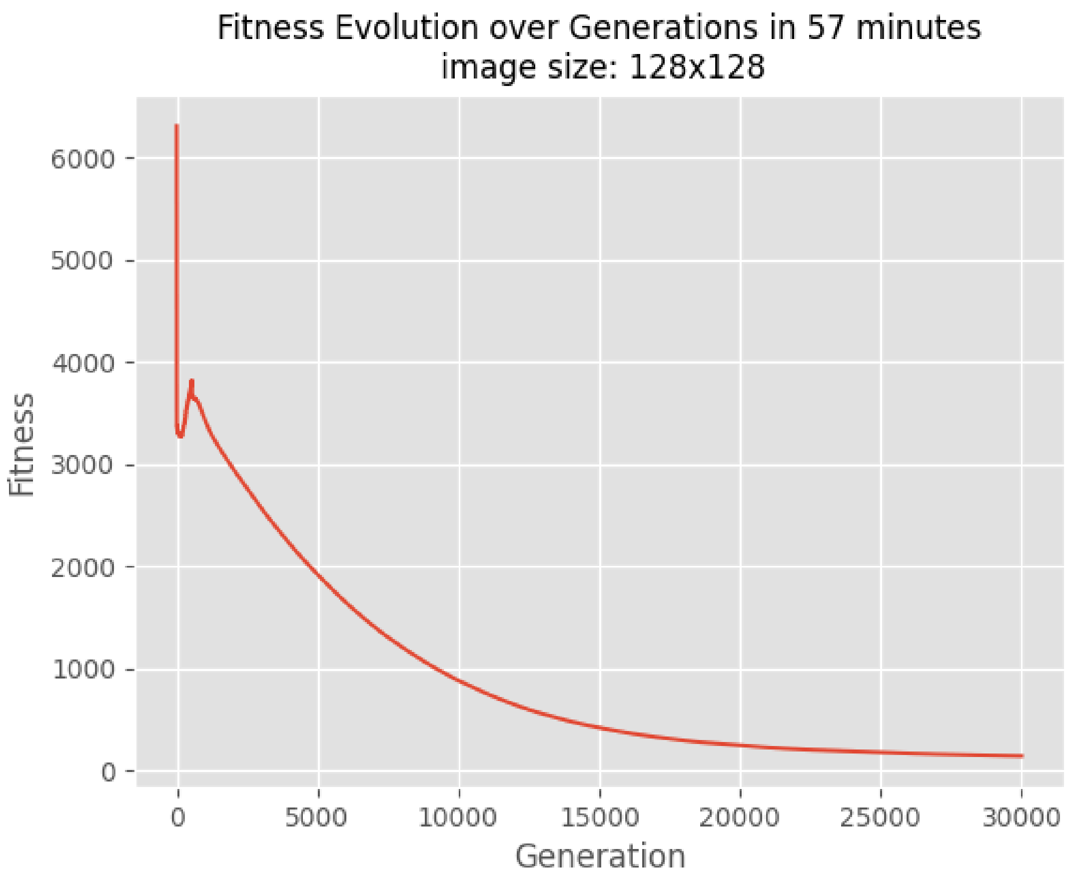
Best Individual

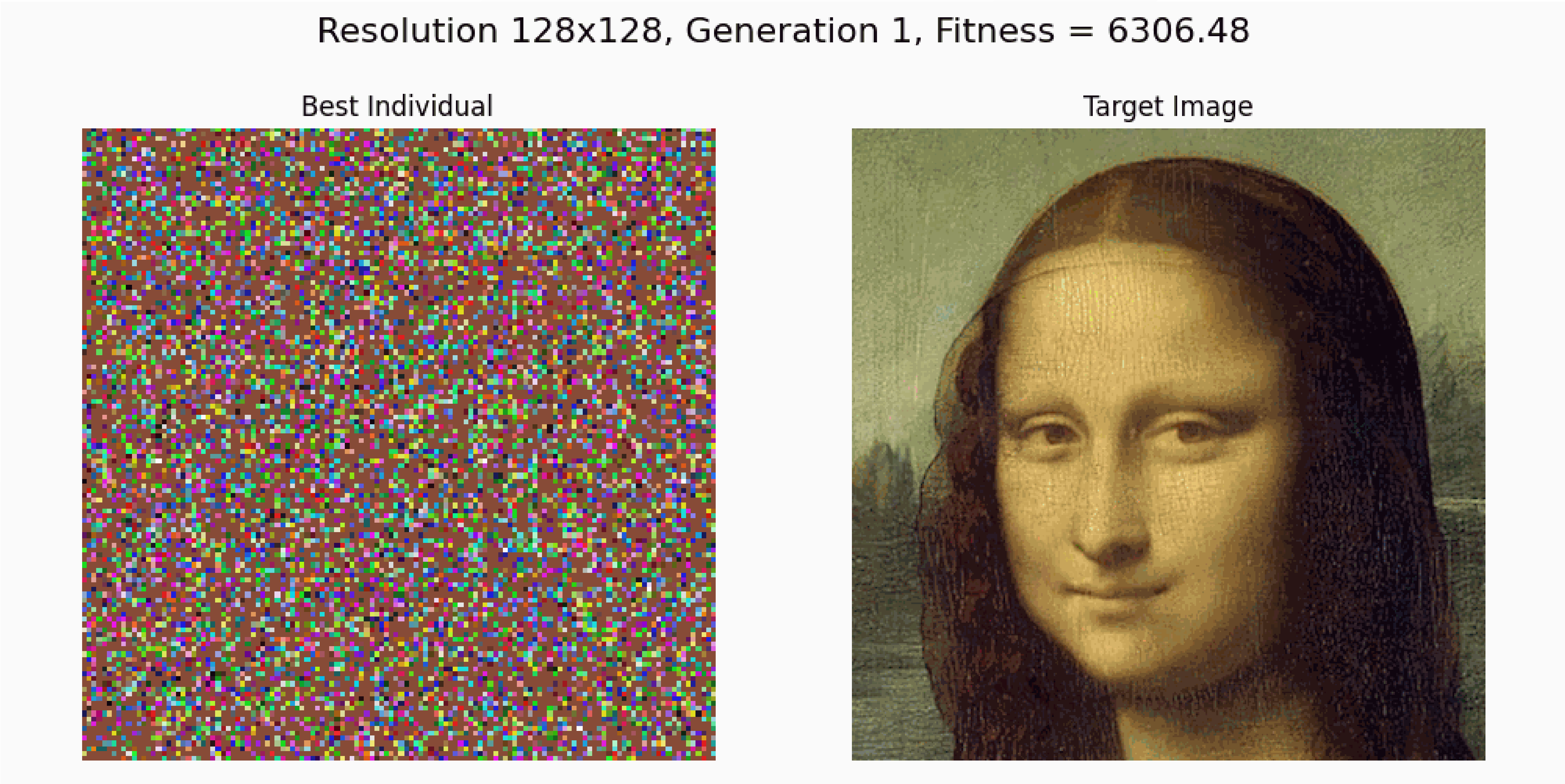


Target Image

128x128px image

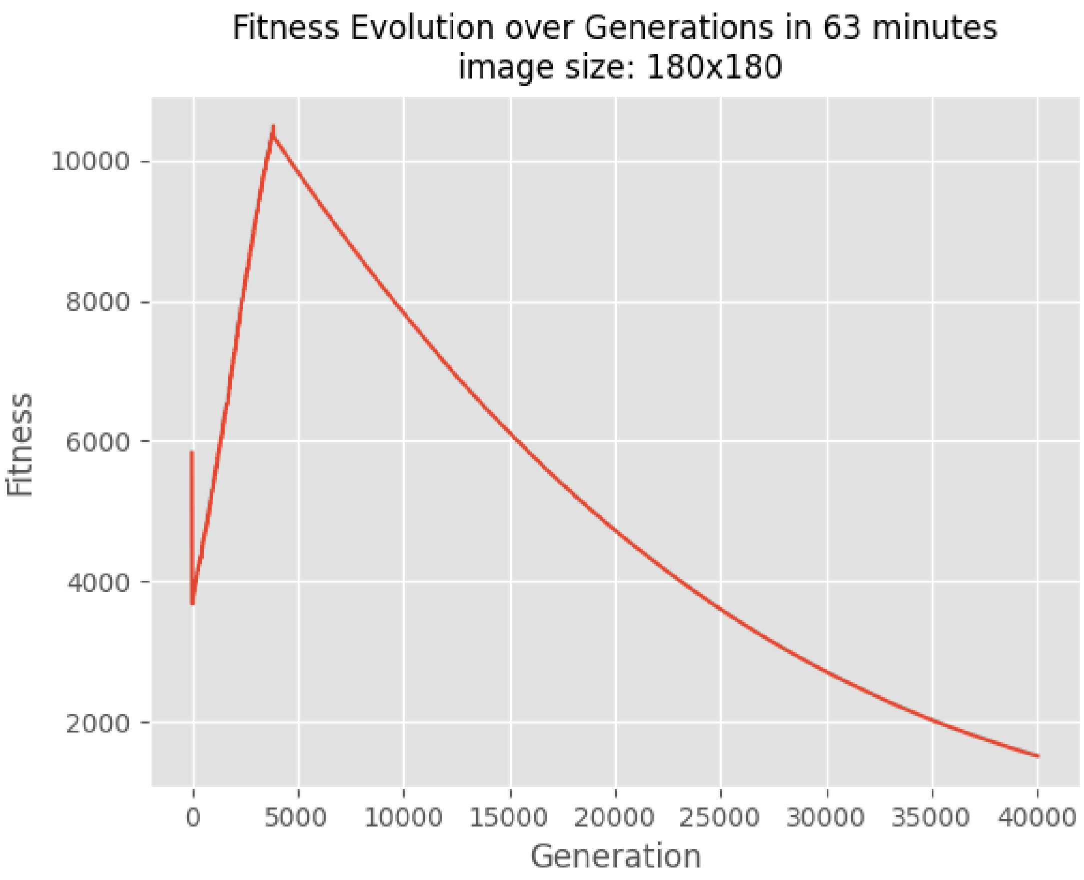
```
pop_size = 100, generations = 30000, mutation_rate = 0.5,
max_mutation_rate = 0.5, tournament_size = 8, replacement = 20,
min_mutation_rate = 0.0005, stagnation_limit = 30, exit_limit=200, n = 128, fit = 'mse')
```




Resolution 128x128, Generation 1, Fitness = 6306.48
Best Individual
Target Image

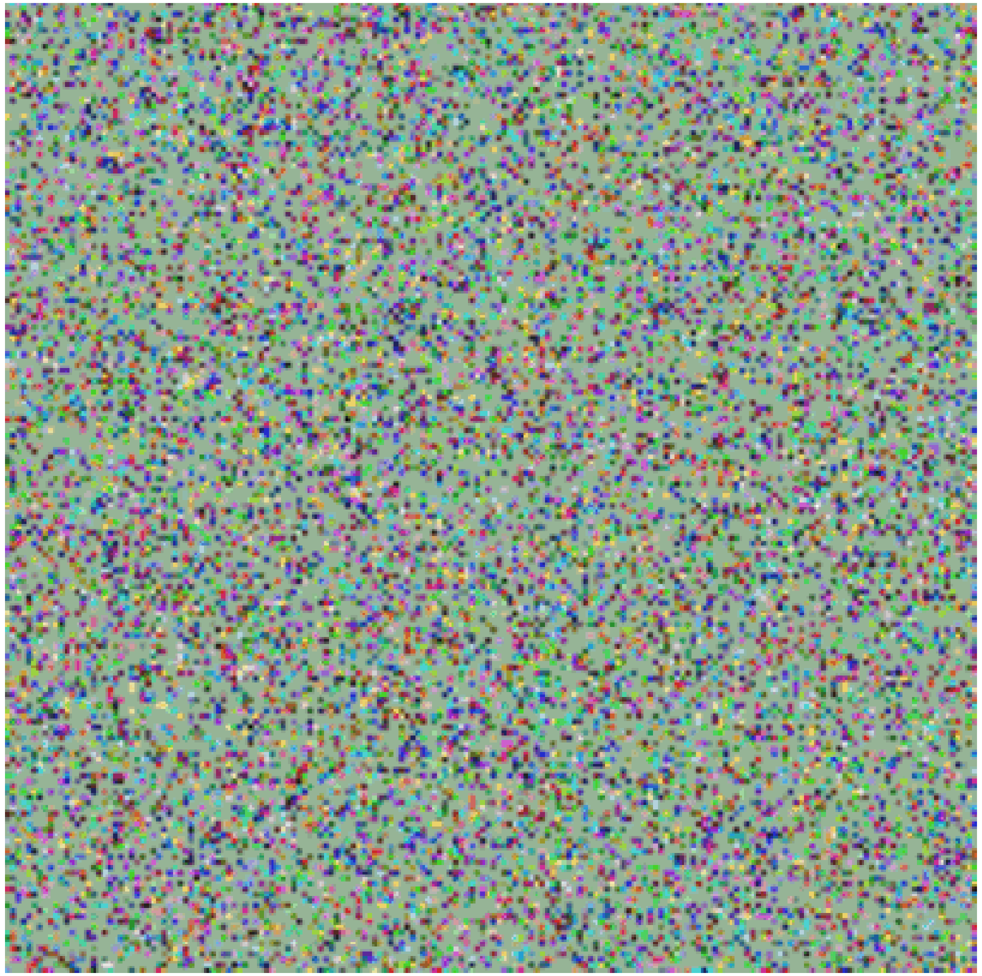
180x180px image

```
pop_size = 100, generations = 40000, mutation_rate = 0.5,
max_mutation_rate = 0.7, tournament_size = 8, replacement = 10,
min_mutation_rate = 0.0005, stagnation_limit = 60, exit_limit=1000, n = 180, fit = 'mse')
```



Resolution 180x180, Generation 1, Fitness = 5831.25

Best Individual



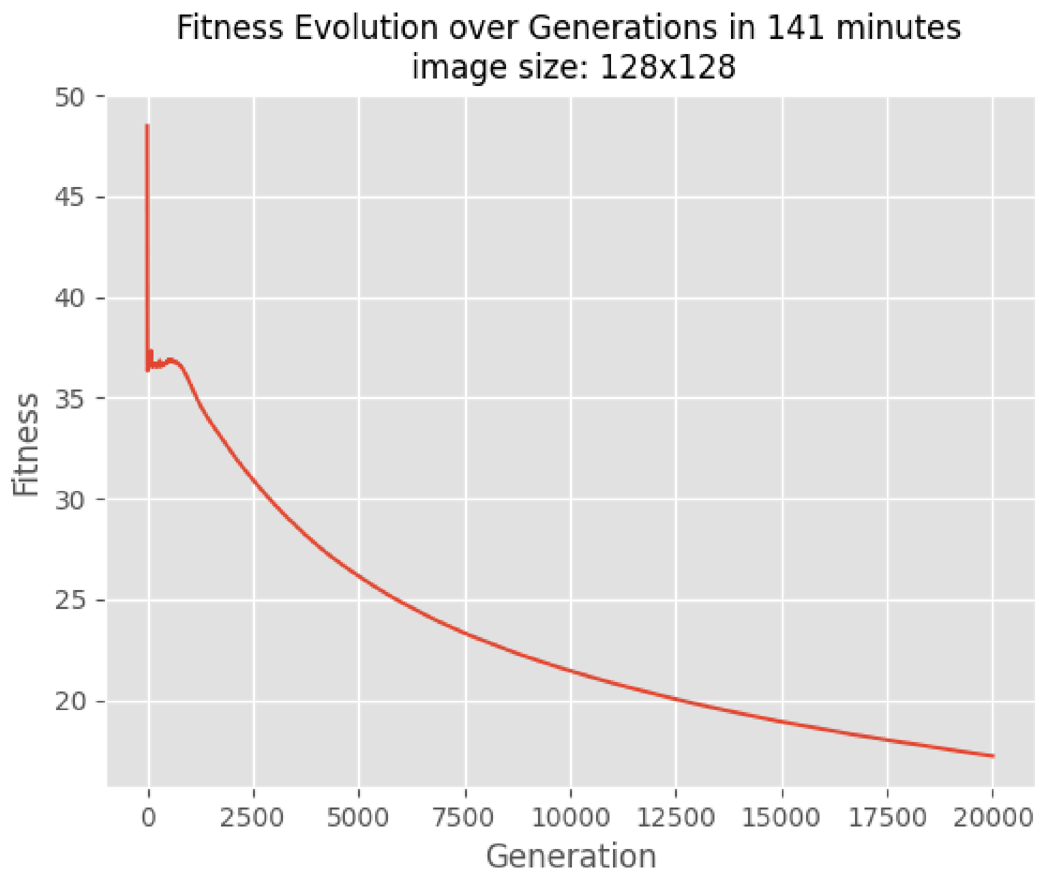
Target Image

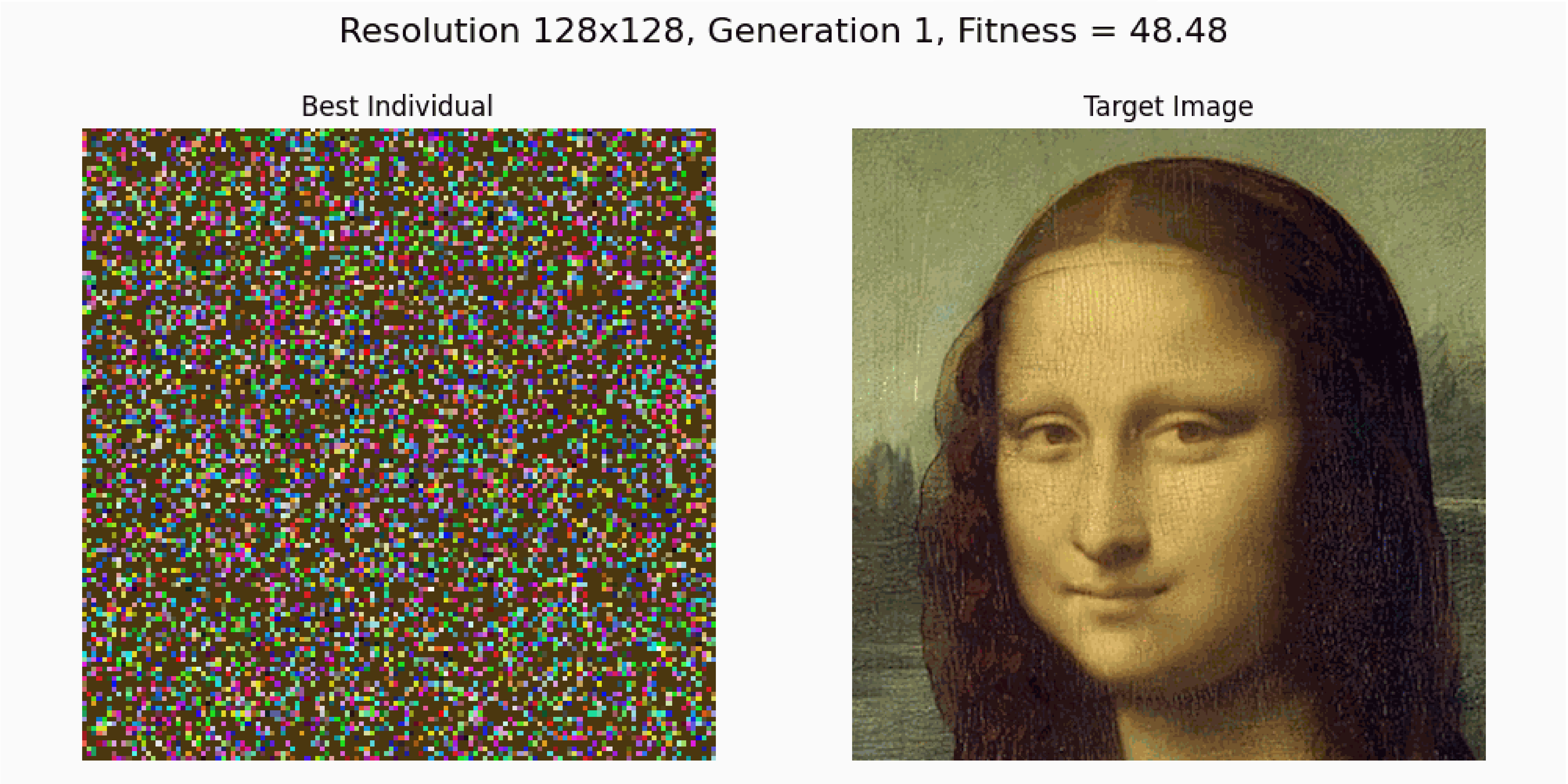
Results (ΔE_{ab})

- Results using ΔE fitness function are not good as expected
- Convergence is slower and inefficient
- Visual results are worse than using MSE

128x128px image

```
pop_size = 100, generations = 20000, mutation_rate = 0.5,
max_mutation_rate = 0.5, tournament_size = 8, replacement = 20,
min_mutation_rate = 0.0005, stagnation_limit = 30, exit_limit=200, n = 128, fit = 'deltaE')
```




Resolution 128x128, Generation 1, Fitness = 48.48
Best Individual
Target Image

Possible causes

- Slower convergence possibly due to the conversion from RGB space to CIE-Lab space

```
from skimage.color import rgb2lab
    # Delta E
if type == "deltaE":
  ind = rgb2lab(individual / 255) # normalisation in [0,1] and conversion
  tar = rgb2lab(target / 255)
  delta_e = np.sqrt(np.sum(np.square(tar - ind), axis=-1))
  fit = np.mean(delta_e)
```

- Possible numeric comparison evaluation diffuclties due to the smaller range $[0, 100]$
- Possible wrong implementation of the fitness function

Conclusions and futher improvements

- MSE showed nice results even though it could not be an optimal fitness for the problem
- Results up to (128x128)px are satysfying with affordable computation times (~ 50 minutes) otherwise more efficient strategies would be needed
- The impact of the crossover techniques could be studied to possibly optimise and lighten up the evolution process by allowing only some of them
- Futher tests using ΔE fitness improving its implementation

THANKS FOR THE ATTENTION