Convolutional Autoencoder with gamma correction module (GAE) for automatic image colorization

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PROJECT PRESENTATION

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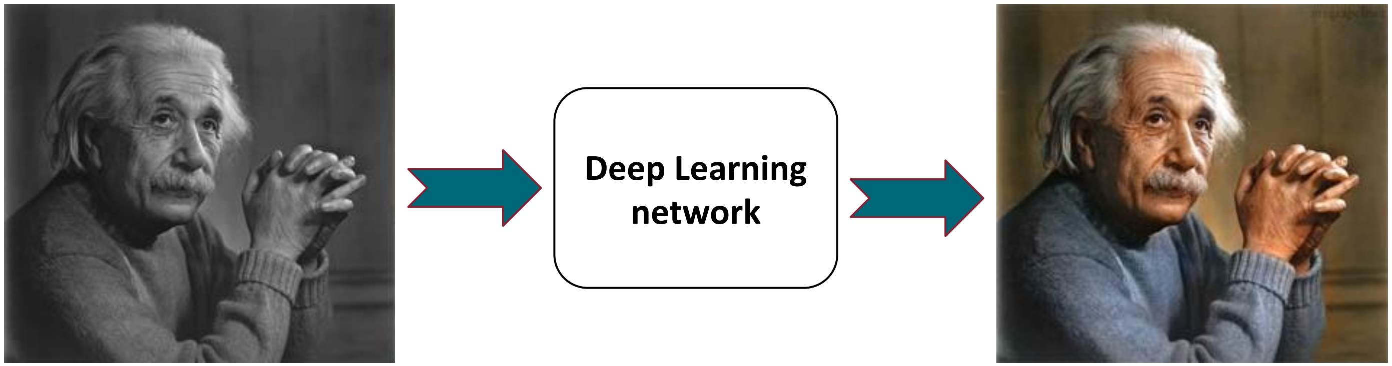
Outline:

- Introduction
- Related Works
- Proposed methods
- Datasets and Metrics
- Implementation details
- Experimental results
- Conclusion and Future Works

Deep Learning Image Colorization



- ➢ **Improving many computer vision tasks by augmenting feature extraction, contrast, and interpretability.**

1. **Historical and cultural restoration**
2. **Enhancing medical imaging**
3. **Object Detection & Scene Understanding**

(and much more …)

Related Works

- **Early Approaches**
  - _Levin et al_. (2004): Scribble-based optimization
  - _Irony et al_. (2005): Image retrieval for color transfer
- **CNN-Based Methods**
  - _Zhang et al_. (2016): End-to-end CNN with classification loss
  - _Iizuka et al_. (2016): Global-local context model
- **GAN-Based Colorization**
  - _Nazeri et al._ (2018): Adversarial learning for vibrant colors
  - _Cao et al_. (2017): User-guided GAN for interactive colorization
- **Transformer & Diffusion Models**
  - _Kumar et al_. (2021): Colorization Transformer
  - _Liu et al._ (2023): Diffusion models for semantic colorization

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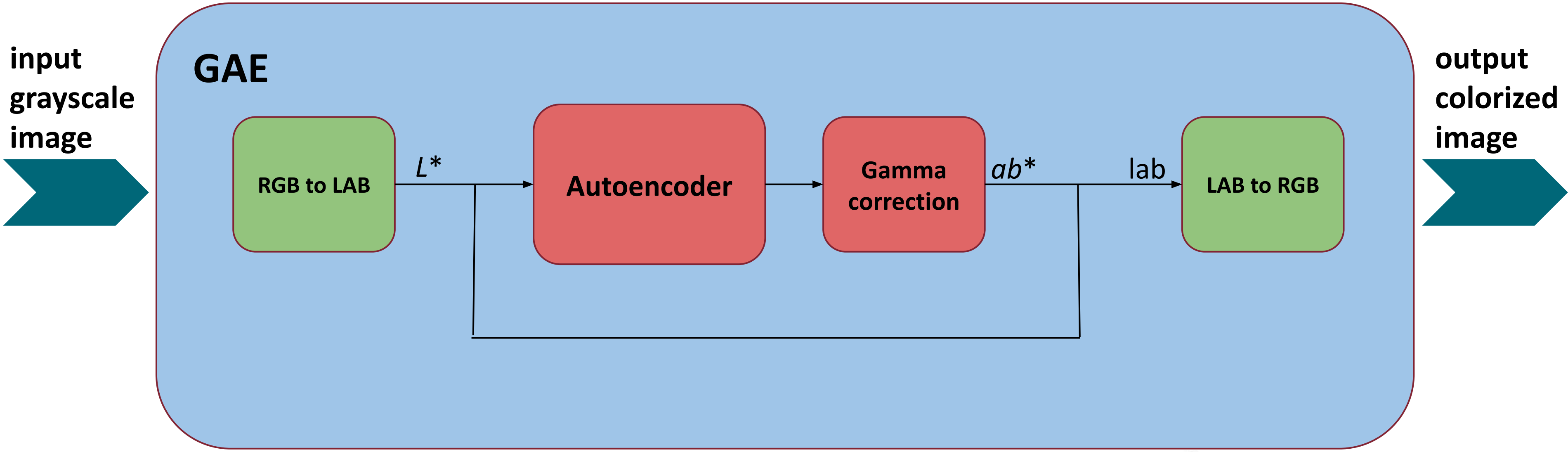
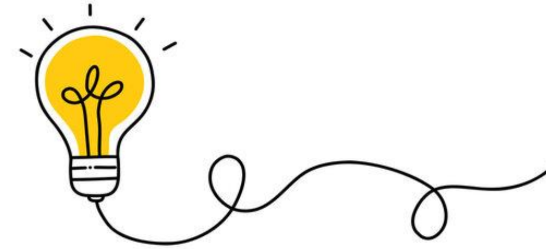
Proposed Architecture (GAE)





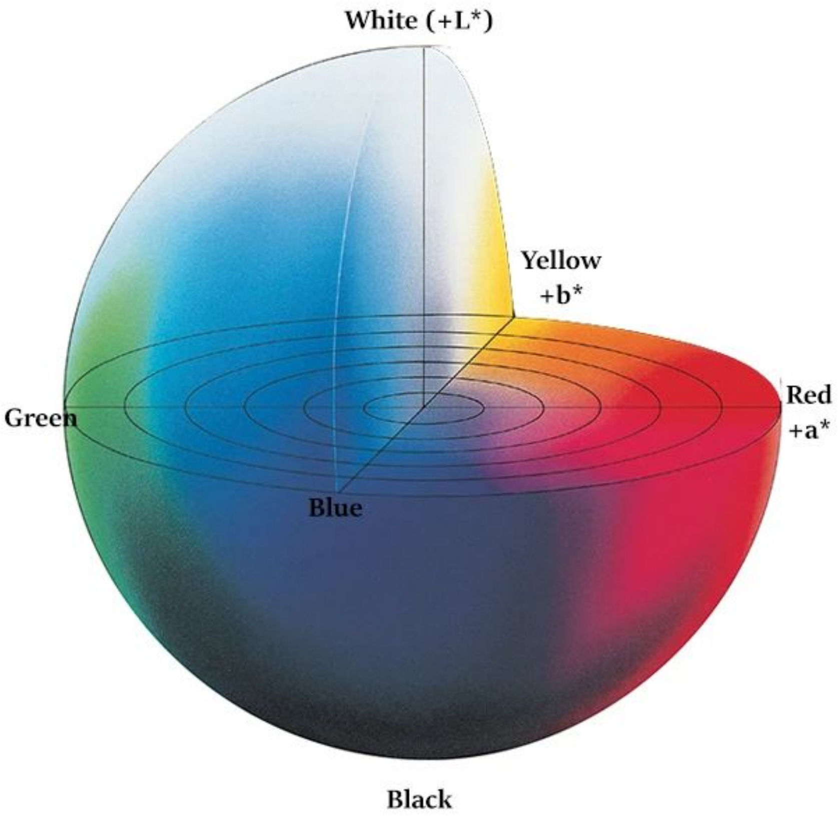
LAB Color Space

- designed to match **human vision** closer than rgb
- LAB color has 3 components:

  L* → Lightness (0 = black, 100 = white)

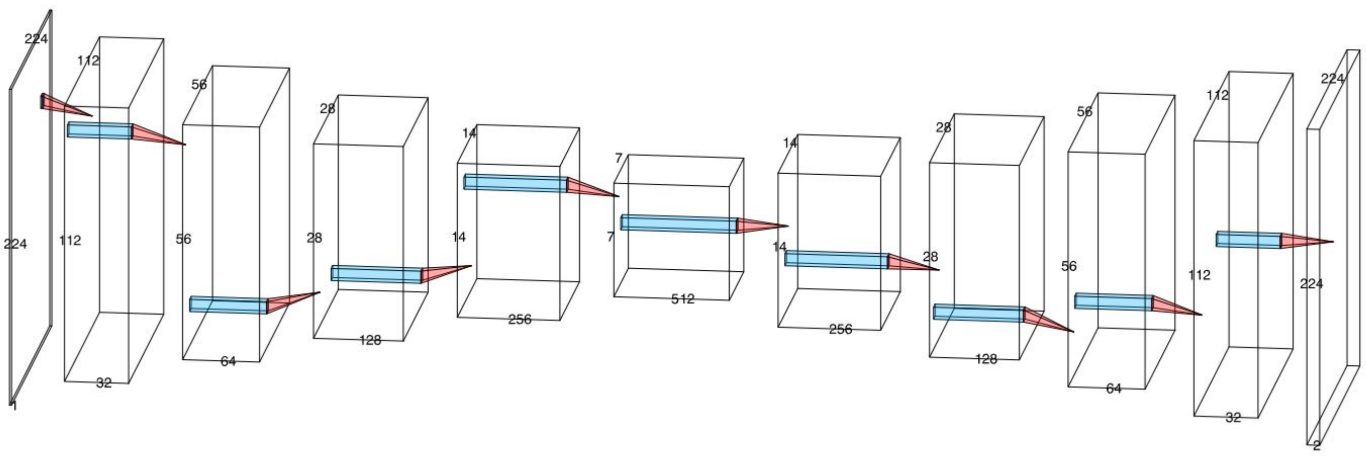
  A* → Green–Red axis (-128 = green, 127 = red)

  B* → Blue–Yellow axis (-128 = blue, 127 = yellow)
- color information stored in only 2 channels(ab)
- widely used in **colorization tasks**



Autoencoder architecture

- **symmetric** 10-layer convolutional autoencoder
- **batch normalization** after every encoder layer
- upsampling through **deconvolution** in decoder
- **Tanh** final activation function to predict a*b* channels (normalized in [-1,1])



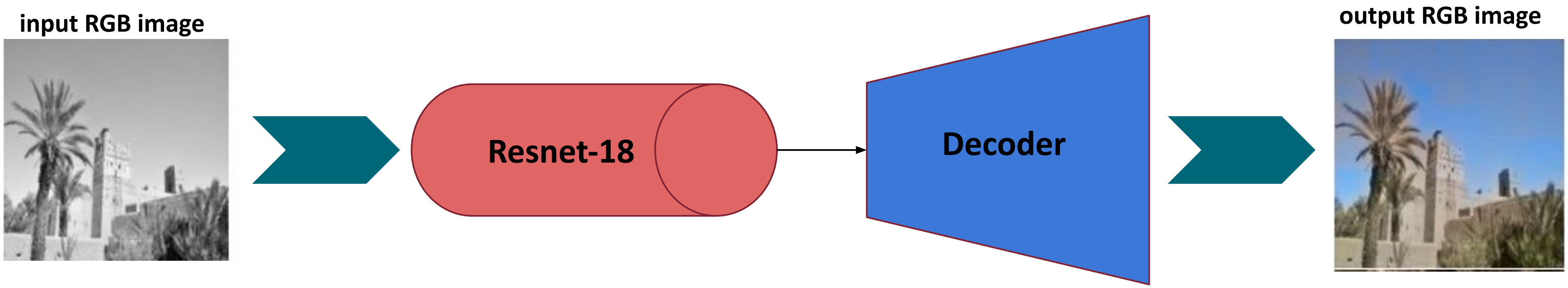
Gamma Correction

- empirically I noticed that colorized images often are very **dull** and **unsaturated,** as the model does very conservative predictions in order to minimize loss

$$X_{out} = X_{in}^{\gamma}$$

- non linear operator to enhance colorization, augmenting **saturation** and **contrast**
- **learnable** γ (initialized to 1)

Baseline



- *Resnet-18* model as a **fixed feature extractor**
- Feature fed directly to **decoder-only** architecture
- faster training, but worst results as only the decoder part is trained for the colorization task

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Dataset

- small subset of the **Places dataset,** which contains 10 million images from diverse environments, from natural landscapes to urban settings.

- **30K** image dataset divided in a **70-15-15** split
- resized images to **224x224**
- **data augmentation:** random rotation, flipping and cropping

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Evaluation Metrics

- **pixel-wise** metrics:
  - *MSE*: average squared difference between corresponding pixels.
    $$MSE = \frac{\sum_{i=1}^{n} (x_i - \widehat{x}_i)^2}{n}$$
  - *PSNR* (Peak Signal-to-Noise Ratio): Measures image quality in decibels (dB)
    $$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$
- **perceptual** metrics:
  - *SSIM*: measures luminance, contrast, and structure similarity.
    $$\mathrm{SSIM}(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$
  - *ΔE(76)*: measures perceptual color difference
    $$\Delta E_{ab}^{*} = \sqrt{(L_2^* - L_1^*)^2 + (a_2^* - a_1^*)^2 + (b_2^* - b_1^*)^2}$$

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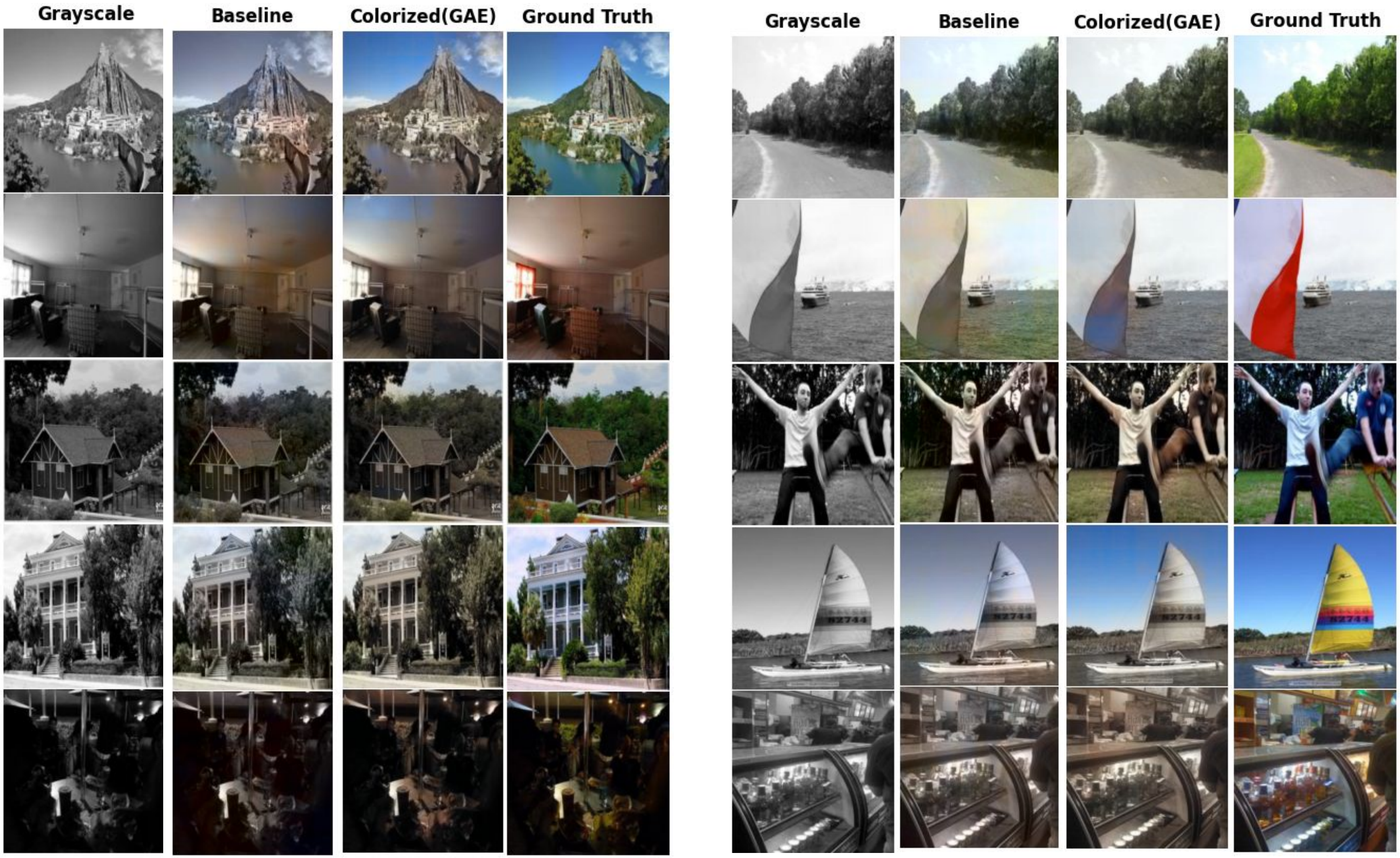
Results: Baseline Comparison

- model tested on **test set** (4500 images) and compared with baseline

	MSE ↓	PSNR ↑	SSIM ↑	ΔE ↓
baseline	0.0063	23.7471	0.9189	13.9822
GAE	**0.0057**	**24.5263**	**0.9408**	**12.9247**

- The proposed architecture outperforms the baseline in every metric by a substantial margin

Results: Colorized Images



Results: Different Experiments

- model trained on more than 4000 **nature/landscapes** images

- model trained on a 5k subset of the **CelebA** dataset

Historical photograph colorization

- since there exists no ground truth, the results are very hard to judge, but promising

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Conclusions and future works

Even though results cannot be comparable to the state of the art, my model is successfully able to colorize images in a **natural** and **vibrant** way, while being relatively **lightweight**. Future improvement might include:

- **Increasing** number of images in **training data** for better generalization
- Use **perceptual loss** for more realistic colors
- **Finetune** model on **different datasets** for different application
- Extend model in order to colorize **videos**

THANKS FOR THE ATTENTION!!

References

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