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Final Project

PROJECT TITLE

Grayscale Image Transformer

To convert grayscale images to colorized versions using GAN

AGENDA

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PROBLEM STATEMENT

Despite the vast amount of historical and monochrome imagery available, there is a significant challenge in revitalizing these images to **convey their original vibrancy and context accurately. Manual colorization processes** are **time-consuming** and often result in subjective outcomes. Thus, there is a need for **an efficient and accurate automated tool for colorizing black and white images** while preserving their authenticity and historical significance.

PROJECT OVERVIEW

The project aims to develop an automated **Grayscale image transformer tool utilizing WGAN** (Wasserstein Generative Adversarial Network) . Leveraging state-of-the-art techniques, the tool will provide users with a seamless and efficient way to **transform monochrome images into vibrant, colored counterparts** while preserving their original context and authenticity.

The tool will cater to diverse applications such as **historical image restoration, artistic enhancement, and multimedia content creation**.

Through rigorous testing, user feedback incorporation, and continuous improvement, the project seeks to deliver a **reliable and versatile** solution **for colorizing black and white images**, contributing to **advancements** in **image processing technology** and **historical preservation efforts.**

WHO ARE THE END USERS?

1. **Historians and Researchers:**
   Utilizing colorization for deeper insights into historical imagery.

2. **Artists and Designers:**
   Enhancing creative projects with colorized sketches and illustrations.

3. **Photographers and Filmmakers:**
   Restoring and adding visual interest to archival footage and photographs.

4. **General Users:**
   Preserving personal memories and sharing black and white images in a vibrant format.

SOLUTION AND ITS VALUE PROPOSITION

The solution leverages a **Wasserstein Generative Adversarial Network (WGAN)** to perform **grayscale image transformation.** It is trained on a dataset of grayscale images paired with their corresponding colorized versions. The model learns to generate realistic colorizations **by minimizing the Wasserstein distance** between the distribution of generated colorized images and the distribution of real colour images. This approach ensures that the generated colorizations **maintain the original context and authenticity** of the grayscale input images.

Value Proposition: Time-saving, Accuracy, Versatility, Enhancing Creativity, Accessibility

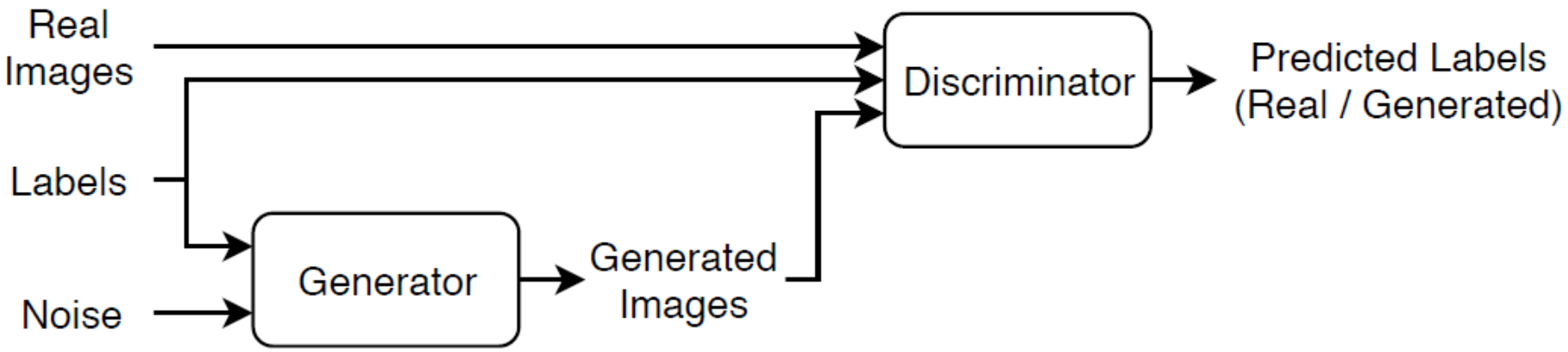
THE WOW IN YOUR SOLUTION

The colorization tool's "wow" factor, driven by **Wasserstein Generative Adversarial Network (WGAN),** lies in its seamless transformation of black and white images into vibrant, lifelike representations.

Unlike traditional GANs, **WGAN's stability** is ensured by using the **Wasserstein distance** as the **loss function**, allowing for smoother optimization. Additionally, WGAN's 1-Lipschitz constraint on the critic **enhances its ability to discern subtle differences**, resulting in **accurate and detailed colorizations** that preserve the original image's essence and detail.

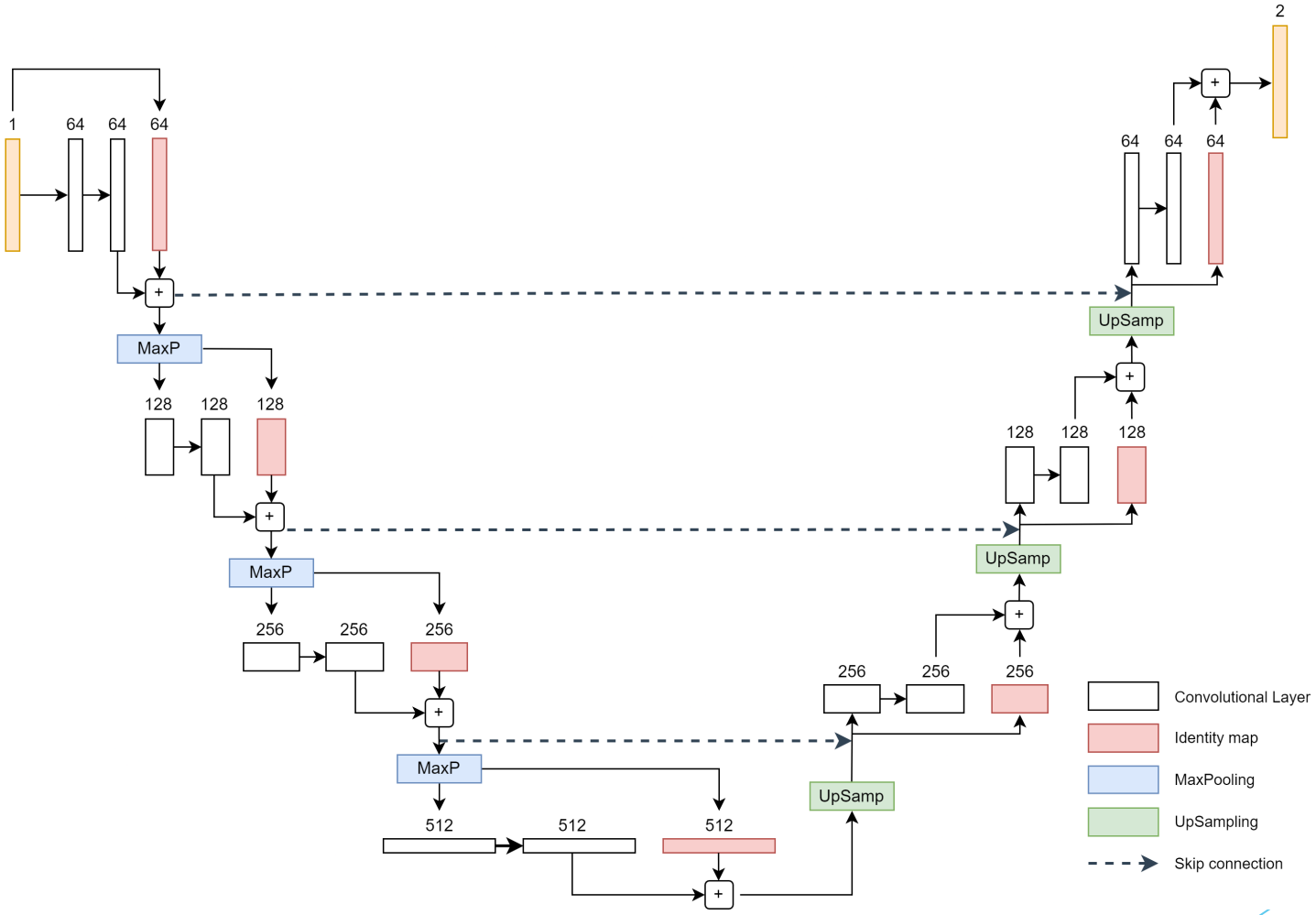
MODELLING

CONDITIONAL GENERATIVE ADVERSIAL NETWORK



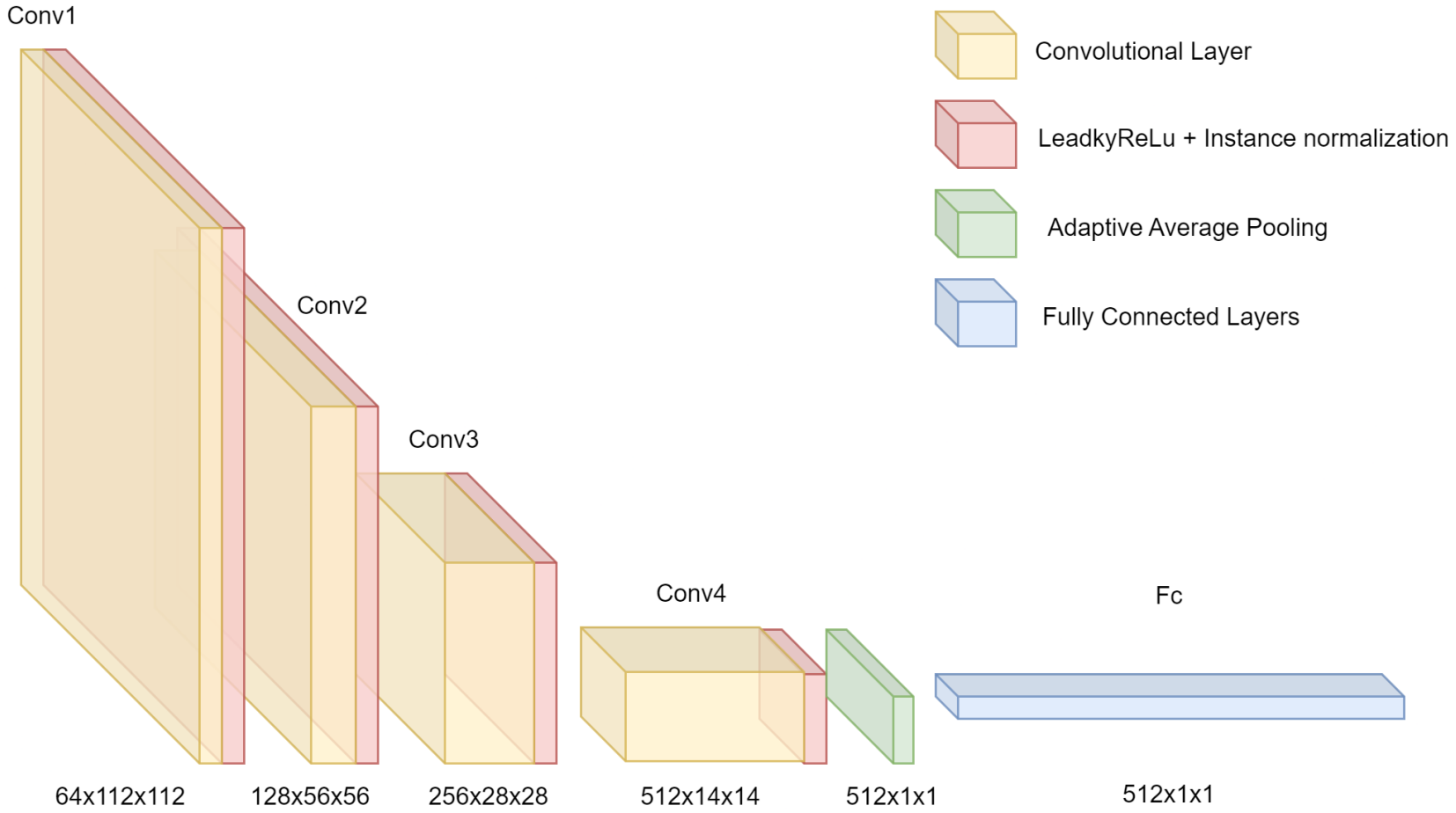
MODELLING (cont)

Generator (ResU-NET)



MODELLING (cont)

Discriminator (Critic)



RESULTS

1. Human Scoring:
    1. Human scorers label each image as real or fake.
    2. Utilizes platforms like Amazon Mechanical Turk for scoring.
    3. Provides qualitative insights into image realism.

2. Inception Score (IS):
    1. Uses a pre-trained Inception model to classify generated images.
    2. Measures both image quality and diversity.
    3. Higher entropy indicates better performance.

3. Frechet Inception Distance (FID):
    1. Compares real vs. generated image distributions.
    2. Lower values indicate better quality and diversity.
    3. More robust to noise and mode collapse.

RESULTS (CONT)

1. Inception score

```
# Calculate the Inception Score
mean_real, std_real = is_model.calculate_is(all_real)
print("Inception Score of real images: mean: {:.4f}, std: {:.
4f}".format(mean_real, std_real))
mean_is, std_is = is_model.calculate_is(all_preds)
print("Inception Score of fake images: mean: {:.4f}, std: {:.
4f}".format(mean_is, std_is))
```

```
Inception Score of real images: mean: 4.1913, std: 1.7591
Inception Score of fake images: mean: 4.2828, std: 1.9007
```

RESULTS (CONT)

2. Frechet Inception Distance (FID):

In [106]:

```
# Initialize the FID class
device = "cuda" # or "cpu" if you don't have a GPU
fid_calculator = FID(device)

# Calculate the FID
fid_value = fid_calculator.calculate_fid(all_real, all_preds)
print("FID: {:.4f}".format(fid_value))
```

```
FID: 36.9385
```

CONCLUSION

In conclusion, **GRAYSCALE IMAGE TRANSFORMER** is a powerful model for specific applications such as colorization.
Using Wasserstein GAN (WGAN) and a U-Net architecture based on residual blocks are two ways to improve the performance of the tool for colorization.

WGANs use **the Wasserstein distance metric** to train the generator and discriminator which can help stabilize the training process and **produce more realistic results**. A **U-Net architecture** which is **well-suited for image segmentation tasks** combined with Residual blocks allows the network to learn **fine details of the input image**, which can be particularly **useful for colorization tasks**.

This can help **improve the stability** and the ability **to learn fine details** of the input image, producing more **realistic results.**