RAG-Enhanced Comic Panel Colorization Using GANs: A Retrieval-Augmented Approach for Context-Aware Automatic Colorization

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Jaspreet Singh | MSIT | 18-19 Nov. 2025

Prakhar Chandra, Pulkit Kapur

Abstract

- This paper serves as a proof-of-concept for RAG-enhanced comic colorization using GANs for better contextual color guidance.

- Automatic comic colorization suffers from inconsistent colors due to missing contextual cues in grayscale panels.

- We propose a **Retrieval-Augmented Generation (RAG)** + **GAN** pipeline to provide contextual color guidance.

- A **U-Net GAN baseline** is first trained, followed by **RAG-enhanced fine-tuning** using CLIP-based visual similarity retrieval.

- A curated reference set (100 images) is created using **K-means clustering** on 1,900 paired, colored comic panels.

- Top-3 retrieved CLIP embeddings (1536-dim) are fused into the generator's bottleneck via learned embedding layers.

- RAG improves validation L1 loss from **0.42 → 0.37**, with visibly better color consistency and palette coherence.

- Establishes a foundation for context-aware creative AI for comics and visual storytelling.

Introduction

- Comics rely on **consistent character colors**, emotional tones, and narrative-driven palettes.

- Manual colorization is labor-intensive and requires artistic expertise.

- Existing GAN-based colorizers often show:

- Arbitrary color choices

- Poor consistency across sequential panels

- Lack of semantic understanding

- **Key problem:** Grayscale panels contain *no color clues*.

- **Idea:** Add external context via *retrieval* to guide color generation.

- **Our contribution:**

- RAG + GAN hybrid for automatic comic colorization

- CLIP-based retrieval for semantic color reference

- Learned embedding fusion for context-aware colorization

Literature Survey and Problem Statement

- **GAN-Based Image Colorization**
  1. Pix2Pix: paired translation using U-Net + PatchGAN
  2. CycleGAN: unpaired translation
  3. Anime/comic colorizers exist but lack context-based consistency

- **CLIP for Visual Similarity**
  1. CLIP embeddings capture **semantic + structural similarity**
  2. Used in style transfer and creative generation
  3. No major work applying CLIP retrieval to comic, or in general, image colorization.

- **Retrieval-Augmented Generation (RAG)**
  1. Introduced for knowledge-intensive NLP tasks
  2. Successful in diffusion models & image editing
  3. Not yet explored for GAN-based colorization tasks

Proposed Methodology

1. Two-Stage Pipeline
- **Stage 1:** Train baseline U-Net GAN
- **Stage 2:** Enable embedding fusion + fine-tune with retrieved CLIP context
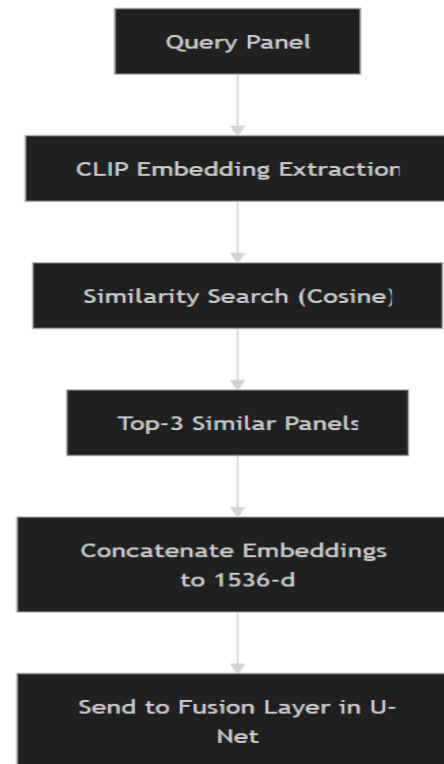
2. CLIP-Based Retrieval
- Compute embeddings for all 1,900 colored panels
- K-means (k = 100) → representative reference set
- Retrieve top-3 matches using cosine similarity
- Concatenate embeddings → **1536-dim context vector**

3. Embedding Fusion
- Project context vector → 512-dim
- Inject into U-Net bottleneck via additive fusion
- Guides generator toward contextually plausible colors

4. GAN Architecture
- U-Net generator (64→1024 channels)
- PatchGAN discriminator
- Loss = L1 + perceptual + TV + adversarial

Query Panel

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CLIP Embedding Extraction

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Similarity Search (Cosine)

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Top-3 Similar Panels

↓

Concatenate Embeddings to 1536-d

↓

Send to Fusion Layer in U-Net

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{adv}} + \lambda_{L1}\mathcal{L}_{L1} + \lambda_{\text{perc}}\mathcal{L}_{\text{perc}} + \lambda_{\text{tv}}\mathcal{L}_{\text{tv}}$$

where

$$\mathcal{L}_{\text{adv}} = \mathbb{E}\left[\log D(x_{bw}, y_{color})\right] + \mathbb{E}\left[\log\left(1 - D(x_{bw}, G(x_{bw}))\right)\right]$$

$$\mathcal{L}_{L1} = \mathbb{E}\left[\|y_{color} - G(x_{bw})\|_1\right]$$

$$\mathcal{L}_{\text{perc}} = \mathbb{E}\left[\|\phi_{\text{VGG}}(y_{color}) - \phi_{\text{VGG}}(G(x_{bw}))\|_1\right]$$

$$\mathcal{L}_{\text{tv}} = \text{TV}\left(G(x_{bw})\right)$$
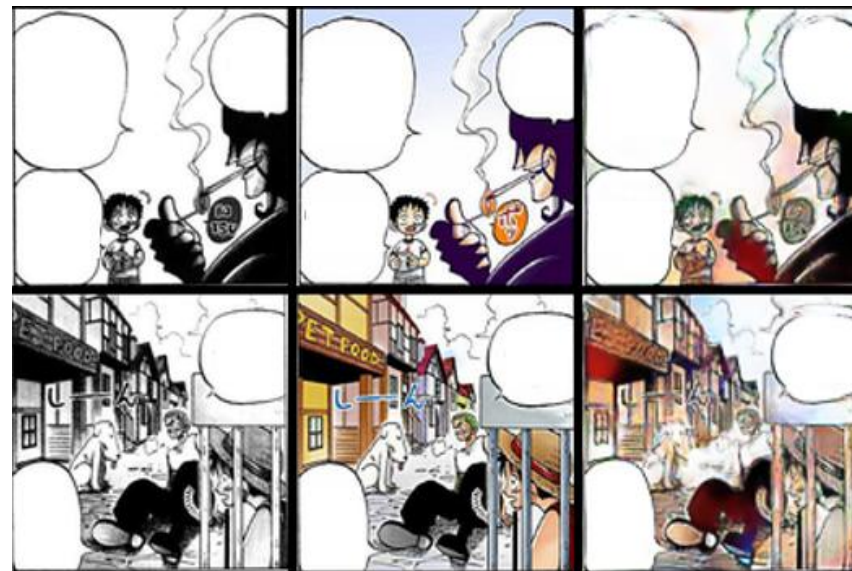
Experimental Setup

- **Dataset**
  - 1,900 paired grayscale–color comic panels
  - 90/10 train/validation
  - 128×128 resolution
  - Augmentations: horizontal flip, light rotation
- **Training Setup**
  - PyTorch + AMP
  - Batch size: 16
  - Adam (LR = 2e-4)
  - 50 epochs total (baseline + fine-tuning)
  - Multi-GPU training (DataParallel)
- **Reference Database**
  - CLIP ViT-B/32 embeddings (512-d)
  - K-means = 100 clusters
  - Precomputed normalized embeddings for fast retrieval

Results and Discussion

- **Quantitative Results**
  1. **Baseline L1 Loss:** 0.42
  2. **RAG-Enhanced L1 Loss:** 0.37
  3. ≈12% improvement
- **Qualitative Observations**
  1. Consistent character colors
  2. Better background & environment realism
  3. Improved hue/saturation stability
  4. Semantic correctness from retrieved color cues
- **Training Behavior**
  1. Smooth GAN convergence
  2. No mode collapse
  3. Embedding fusion integrates context without instability
- **Overhead**
  1. +5% additional training time
  2. Negligible extra inference overhead

Conclusion and Future Scope

Conclusion

- RAG + GAN enables **context-aware comic colorization**.

- CLIP retrieval provides missing color cues, improving consistency.

- Achieves both quantitative & perceptual improvements.

- Demonstrates potential of retrieval-augmented creative AI.

Future Scope

- Higher-resolution colorization (512×512+)

- Attention-based embedding fusion

- Larger reference database

- Dynamic retrieval (variable top-k)

- Cross-panel temporal consistency

- Interactive artist-in-the-loop tools

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