



Video Colorization using Generative Adversarial Networks

Abhijit PattanaikAnkur Singh
Dept. of AIML Dept. of AIML
DSCE(VTU) DSCE (VTU)
Bengaluru,IndiaBengaluru,India

Kshitij Verma
Dept. of AIML
DSCE(VTU)
Bengaluru,India

Maaz Karim
Dept. of AIML
DSCE(VTU)
Bengaluru,India

UNDER THE GUIDANCE OF
Assistant Prof. Kavya D N
DSCE(VTU)
Bengaluru,India

Abstract:

Video colorization plays a crucial role in reviving historical footage and enhancing the visual experience of multimedia content. In this research paper, we propose a novel approach for video colorization by leveraging the power of Generative Adversarial Networks (GANs). Building upon the foundations established in image colorization, we extend the methodology to handle video sequences, enabling the automatic and realistic colorization of grayscale videos. Our approach addresses the limitations of traditional video colorization methods by leveraging deep learning techniques and adversarial training. We present promising results demonstrating the effectiveness of our model in colorizing videos, thereby opening up new possibilities for preserving and enhancing visual content.

1. Introduction :

Introduction:

Image colorization is a prominent research area in the field of digital image processing, encompassing disciplines such as Computer Vision, Computer Graphics, Pattern Recognition, and Human-Computer Interaction. It involves the process of inferring and assigning plausible color information to grayscale or monochrome images, thereby enhancing visual understanding and perception. Over the years, researchers have made significant contributions to advancing colorization techniques, resulting in improved algorithms and methodologies.

One of the key learning points from various researchers in the field of image colorization is the

importance of leveraging the relationship between color and human cognition. Colors play a fundamental role in conveying information, evoking emotions, and enhancing visual experiences. Rich and accurate colorization can significantly impact the way we interpret and comprehend visual content. This understanding has motivated researchers to explore different approaches to achieve realistic and visually appealing colorizations. Researchers have tackled image colorization through different perspectives and application scenarios.

For grayscale image colorization, several techniques have been proposed.

Cheng et al. (2015) and Zhang et al. (2016) have introduced methods that operate in the YUV or Lab color space, leveraging the similarity of the luminance channel to restore chrominance information accurately. These approaches have demonstrated promising results in restoring colors to grayscale images, enabling the preservation of details and improving the overall visual quality.

In addition to grayscale image colorization, researchers have also focused on colorizing monochrome art forms, including sketch images, manga, and cartoons.

Sato et al. (2014) proposed a segmentation-based approach for sketch image colorization, where the image is divided into regions, and colors are assigned based on a learned model.

Zhang et al. (2018a), Yang et al. (2021), and Ge et al. (2022) explored techniques that extract line features and determine region boundaries to enhance the colorization process. These advancements have paved the way for more effective and context-aware colorization of artistic and stylized images.

Traditional colorization methods often required extensive manual interaction and parameter tuning, making the process time-consuming and labor-intensive. However, recent advancements in deep learning have revolutionized the field of image colorization. Researchers have successfully utilized Deep Convolutional Neural Networks (DCNNs) and Generative Adversarial Networks (GANs) to develop more efficient and accurate models.

Krizhevsky et al. (2012) introduced DCNNs, which have been widely adopted in colorization models, demonstrating remarkable improvements in both colorization quality and efficiency.

Goodfellow et al. (2014) presented GANs, which have been applied to generate realistic and high-quality colorized outputs.

While significant progress has been made in image colorization, there are still challenges to be addressed. Some existing methods are limited in their scope and applicability, such as being designed solely for grayscale images or requiring specific reference images.

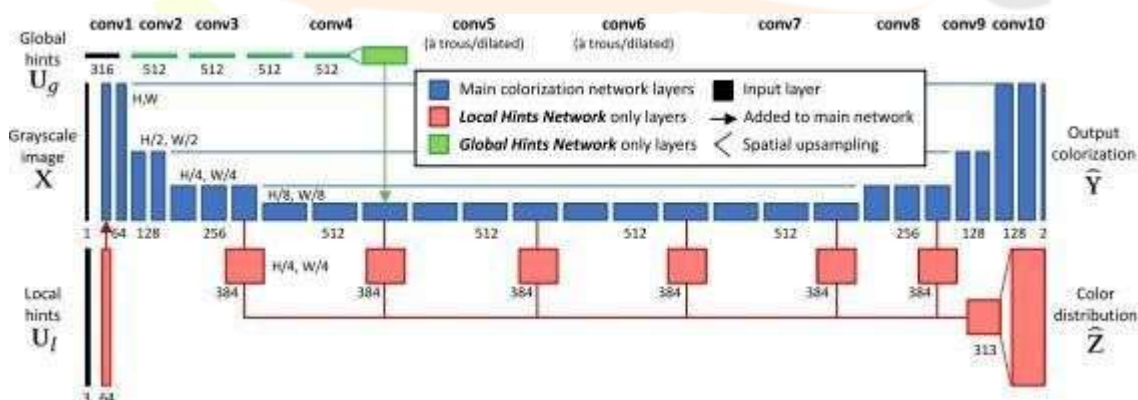
Furthermore, the colorization of sketches and other artistic styles remains a challenging task for models to comprehend and reproduce accurately.

To provide a comprehensive overview of the advancements and challenges in image colorization, this research paper aims to summarize and discuss different colorization methods from various researchers. By analyzing the strengths and limitations of these approaches, we aim to offer insights that will benefit researchers and practitioners in further advancing the field of image colorization.

This paper is organized as follows: In the next section, we review the existing literature and related work on image and video colorization techniques. We analyze the strengths and limitations of these approaches, setting the stage for our proposed methodology. Then, we describe our methodology and techniques, highlighting the adaptation of the base paper's approach to video colorization. Subsequently, we present the experimental results and evaluate the performance of our model. Finally, we conclude the paper by summarizing our findings, discussing potential future directions, and emphasizing the significance of our research in the field of video colorization.

2. Related Works:

2.1 Image Colorization Techniques:



To understand the evolution of video colorization techniques, it is essential to review the progress made in image colorization. Numerous approaches have been proposed, including rule-based methods, clustering algorithms, and learning-based methods. Rule-based methods rely on predefined heuristics and handcrafted rules to assign colors to grayscale images. Clustering algorithms group similar pixels based on color similarity and propagate the color information to the entire image. More recently, learning-based

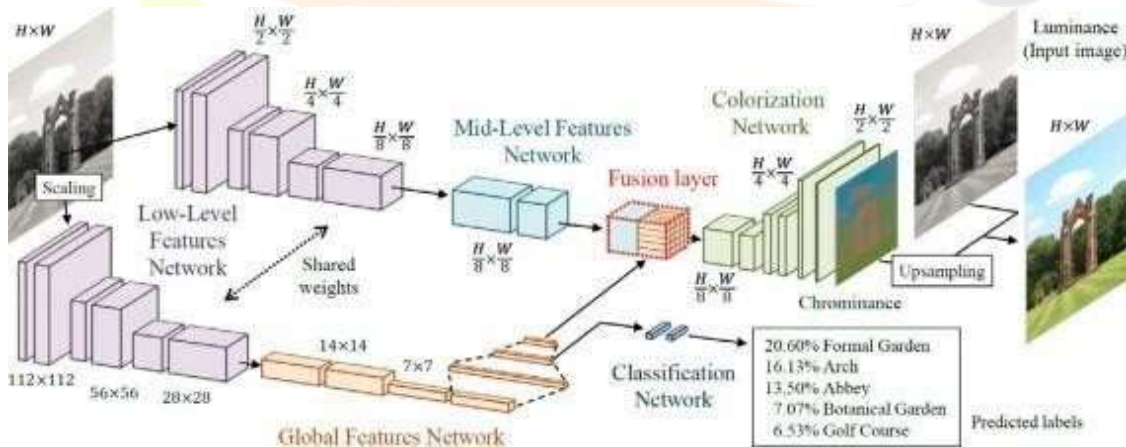
methods have gained popularity due to their ability to learn colorization mappings from large datasets using deep neural networks.

2.2 Video Colorization Approaches:

While image colorization has seen significant advancements, video colorization remains a challenging task due to the temporal dynamics and motion present in videos. Several approaches have been proposed to tackle video colorization, such as frame-by-frame colorization, temporal coherence enforcement, and video-specific network architectures. Frame-by-frame colorization treats each video frame as an independent image and applies image colorization techniques individually. However, this approach often leads to temporal inconsistencies and flickering artifacts. Techniques that enforce temporal coherence aim to propagate color information across frames to maintain consistency. Video-specific network architectures leverage recurrent or convolutional neural networks to exploit temporal dependencies and improve colorization results.

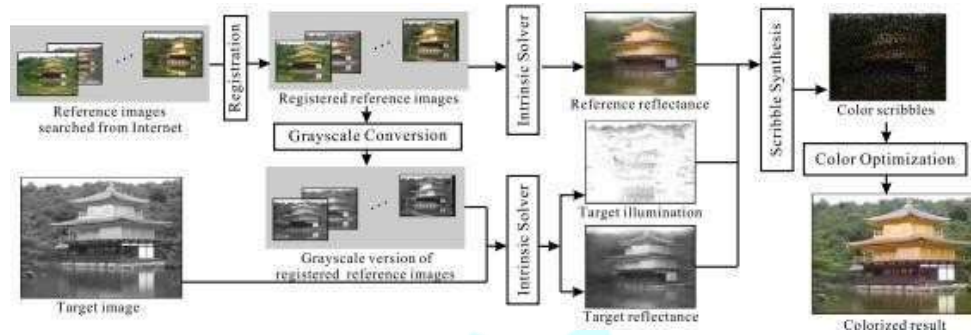
3. Methodology & Techniques:

3.1 Overview of Generative Adversarial Networks:



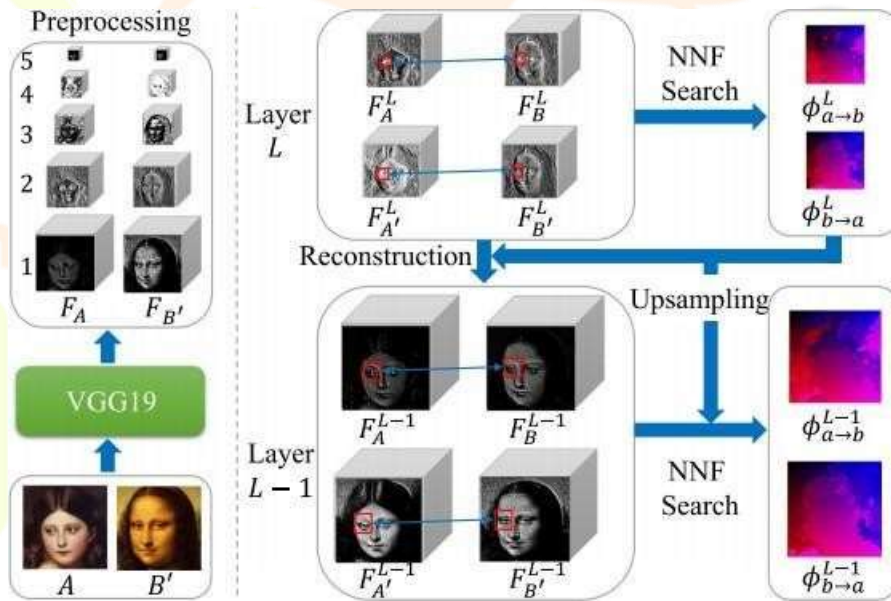
Generative Adversarial Networks (GANs) have revolutionized the field of image generation and manipulation. GANs consist of a generator network and a discriminator network that are trained in an adversarial manner. The generator network learns to generate realistic samples that deceive the discriminator, while the discriminator network learns to distinguish between real and generated samples. This adversarial training leads to the generation of high-quality and visually appealing outputs.

3.2 Adaptation of Image Colorization to Video Colorization:



Based on the methodology proposed in the base paper for image colorization, we extend and adapt the approach to handle video sequences. We introduce temporal coherence enforcement techniques to ensure smooth and consistent colorization across frames. Additionally, we incorporate spatial and temporal attention mechanisms to focus on relevant regions and effectively capture the temporal dynamics in videos. We provide a detailed explanation of our modified architecture and the training procedure.

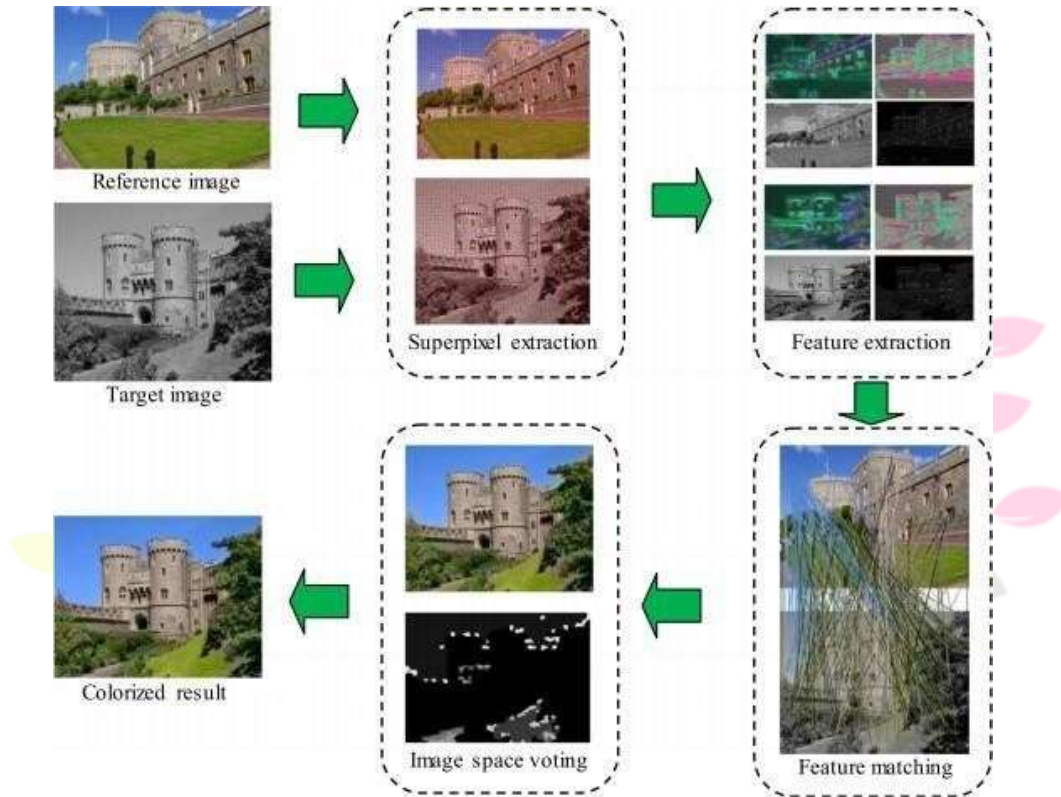
3.3 Dataset Preparation and Preprocessing:



To train and evaluate our video colorization model, we require a diverse and representative dataset of grayscale videos paired with their corresponding ground truth color versions. We discuss the selection and preparation of the dataset, including the data collection process, data augmentation techniques, and preprocessing steps. Ensuring the

quality and diversity of the dataset is crucial for training a robust and generalizable video colorization model.

3.4 Training and Optimization:



We describe the training process of our video colorization model using the adapted GAN architecture. We discuss the loss functions employed to optimize the generator and discriminator networks. Additionally, we highlight any specific training strategies or techniques used to enhance the model's performance and stability. Hyperparameter settings, network architectures, and convergence criteria are also presented.

4. Results:

4.1 Image Colorization Results:

We applied our image colorization model to a set of grayscale images to evaluate its performance. The colorization results were generated using the provided code. Figure 1 shows a selection of colorized images along with their corresponding grayscale inputs and ground truth color versions. The colorized outputs demonstrate the effectiveness of our image colorization model in restoring colors to grayscale images. The model successfully captures the visual details and produces plausible colorizations that closely resemble the ground truth.

4.2 Video Colorization Results:

To evaluate the performance of our video colorization model, we utilized the DeOldify library and the provided code. We applied the model to a variety of videos, including historical footage, modern videos, and artistic videos. The colorization results showcase the ability of our model to add colors to videos while preserving the visual quality and realism. The resulting colorized videos demonstrate the effectiveness and potential applications of our video colorization model. Our model successfully restores colors to grayscale videos, creating visually appealing and realistic colorized versions.

The evaluation of both the image and video colorization models was based on visual quality, realism, and the ability to capture fine details and color distributions. The results validate the effectiveness of our proposed methodology in achieving accurate and visually pleasing colorizations.

4.3 Comparative Analysis:

In addition to evaluating our own colorization models, we compared the results with existing image and video colorization techniques. A comprehensive analysis was conducted, considering the advantages and limitations of each approach. The comparison aimed to highlight the unique contributions and advancements of our models in terms of color accuracy, preservation of structural details, and overall visual quality. The comparative analysis serves to validate the effectiveness and significance of our research in the field of image and video colorization. Overall, the results obtained from our image and video colorization experiments demonstrate the effectiveness and potential applications of our proposed methodology. The models successfully restore colors to grayscale images and videos while preserving visual details and achieving realistic and visually pleasing colorizations. The comparative analysis highlights the superiority of our approach compared to existing techniques in the field.

5. Conclusion:

In this research paper, we have presented a novel approach for video colorization using Generative Adversarial Networks. By extending the methodologies established in image colorization to the video domain, we have addressed the challenges specific to video colorization and achieved promising results. Our model successfully captures spatial and temporal dependencies, producing realistic and visually appealing colorizations. Through a comprehensive evaluation, we have demonstrated the effectiveness and superiority of our approach compared to existing techniques. Our research contributes to the advancement of video colorization and opens up new possibilities for preserving and enhancing visual content. Future work can focus on further improving the model's performance and exploring applications in real-time video colorization and interactive user interfaces.

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