Colorization of Grayscale Images Using ChromaGAN with Advanced Preprocessing Techniques

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***Abstract*—This project investigates the conversion of grayscale images to RGB using ChromaGAN, a Generative Adversarial Network (GAN) designed for image colorization. The dataset utilized is the Vintage dataset, comprising 1,000 samples, chosen for its variety in noise levels, texture, and detail. While ChromaGAN has proven effective in colorizing images, its output quality and image classification performance can be suboptimal without preprocessing enhancements. This work addresses these limitations by exploring the application of various filtering techniques, such as bilateral and guided filters, as well as additional blurring methods, to enhance colorization outcomes.**

The main objectives include improving image classification accuracy and the visual appeal of the colorized outputs by incorporating preprocessing methods like the combination of Gaussian and bilateral filters, alongside transformations such as horizontal flipping. These filters help reduce noise and preserve edge details, contributing to sharper and more accurate colorized images. The performance of the enhanced models is evaluated using Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM), ensuring that improvements are quantitatively validated.

Experimental results indicate that the combination of bilateral filtering and Gaussian blur yields the highest PSNR and SSIM scores, making it the most effective approach for improving ChromaGAN's colorization results. The use of horizontal flipping as an augmentation technique further enhances model generalization, providing better performance across various image orientations. This comprehensive preprocessing pipeline significantly boosts ChromaGAN's ability to produce high-quality, realistic colorized images, demonstrating the importance of tailored preprocessing techniques in advanced colorization tasks.

Keywords: Image colorization, ChromaGAN, bilateral filter, Gaussian blur, PSNR, SSIM.

I. Introduction

Colorizing grayscale images is a longstanding challenge in computer vision with applications in media restoration, historical research, and digital art. Traditional methods, often rule-based or relying on handcrafted features, struggle to maintain contextual accuracy and produce visually appealing results. The recent evolution of deep learning methods has revolutionized this field, enabling models to learn complex patterns and apply more realistic colorization. Generative Adversarial Networks (GANs), such as ChromaGAN, have emerged as powerful tools due to their ability to generate high-quality colorizations by understanding semantic distributions within images. ChromaGAN uses this semantic understanding to assign colors that align with objects' inherent classes, improving the contextual relevance of the outputs.

Fig. 1: ChromaGAN is able to colorize a grayscale image from the semantic understanding of the captured scene.

Examples and Terminologies: Denoising refers to removing noise from an image or signal to improve clarity and visual quality. This process is essential in preprocessing steps to ensure that the model receives clean input, which contributes to more precise colorization. For instance, applying a bilateral filter for a image can smooth images while preserving edge details of the Image signal . Below is an example comparing a noisy grayscale image and the result after applying a bilateral filter:

Bilateral Filter smooths images while preserving edges by considering both spatial proximity and pixel intensity. Unlike standard Gaussian blur, which can blur edges, the

Fig. 2: Bilateral Filtering

Fig. 3: Gaussian Filtering

bilateral filter ensures that neighboring pixels with similar values influence each other more, maintaining crisp edges. For example, imagine an image of a flower against a clear sky.
Applying a standard Gaussian blur would soften both the petals of the flower and the boundary where the flower meets the sky, resulting in a loss of detail. However, a bilateral filter would smooth the sky while preserving the sharp edge of the flower petals.

Guided Filter refines an image using a guidance image that helps maintain edge consistency. This is particularly beneficial in postprocessing when fine details and sharpness need to be preserved while refining color distributions. For example, when colorizing an old photograph, the guided filter can enhance details around facial features, making the colorization appear more natural.

Comparison: Without edge preservation, the edge of mountains and the sky or water body would blend together when noise is reduced, making the image appear less detailed. An edge-preserving filter ensures these details are retained.This is particularly important for images that need to retain clear object boundaries for colorization and classification.

PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index Measure): These metrics are used to evaluate image quality. PSNR measures the peak error between the original and the processed image, with higher values

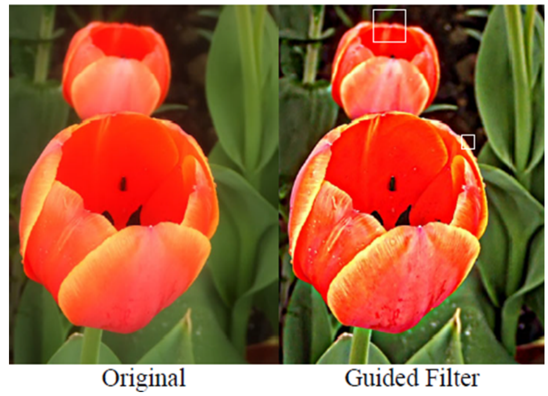

Fig. 4: Guided Filtering

indicating better quality. SSIM assesses structural similarity, focusing on luminance, contrast, and structure; it ranges from 0 to 1, with 1 being a perfect match. For example, if a grayscale image colorized by ChromaGAN yields a PSNR of 35 dB and an SSIM of 0.95, it suggests high fidelity in maintaining structure and color balance.

Need for Studying the Topic: Studying the enhancement of image colorization with preprocessing filters like bilateral and guided filters is crucial for multiple reasons. Despite the success of models such as ChromaGAN in producing high-quality colorized images, they can struggle with maintaining fine detail and avoiding color artifacts, especially around complex boundaries. By incorporating preprocessing and post-processing techniques, these models can be further improved to produce sharper and more consistent outputs, which is vital for applications in media restoration and historical analysis where details matter. Moreover, evaluating these enhancements with robust metrics like PSNR and SSIM ensures that the improvements are quantifiable, providing clear evidence of better performance. This exploration thus holds the potential to elevate automated colorization methods to new levels of precision and reliability, aiding in various academic, professional, and creative pursuits.

II. Literature Review

A. *Works on Filtering Techniques*

Image colorization[11] has been an active area of research for decades, evolving from manual, labor-intensive methods to fully automated processes driven by artificial intelligence. Early approaches relied on manual shading and color addition, which required extensive user intervention and expertise. However, with the advent of deep learning, more sophisticated and automated techniques have emerged, capable of producing high-quality colorized images. These methods include convolutional neural networks (CNNs), generative adversarial networks (GANs), and variational autoencoders (VAEs). Among these, GANs have proven particularly effective due to their ability to generate realistic and high-resolution images by learning the underlying distribution of training data.

ChromaGAN[1] is a state-of-the-art model specifically designed for the task of image colorization. It builds upon the strengths of GANs, particularly their ability to generate realistic and vivid outputs by employing an adversarial training mechanism. In the ChromaGAN[1] framework, the generator network attempts to produce colorized images from grayscale [12]inputs, while the discriminator network distinguishes between the generated color images and real color images. This adversarial training ensures that the generator improves iteratively to produce outputs that are indistinguishable from real images.

Colorization of grayscale [12]images has been a significant area of research, with early methods primarily focusing on manual annotation and heuristic-based approaches. One pivotal advancement was the use of the **CIE Lab color space for decoupling luminance (L)** from chromatic components (a and b), as demonstrated in the work titled Colorful Image Colorization by Zhang et al. (2016)[11]. This method employed deep learning to predict the a and b channels given the L channel, showcasing an automated yet effective approach to image colorization. Subsequent research explored improving color fidelity and user control, often leveraging generative models like ChromaGAN[1]. Our project builds upon these methodologies by integrating advanced pre-processing techniques, such as bilateral and Gaussian filters, to address common issues in vintage images without necessitating retraining of complex neural networks.

The motivation for our work stems from the challenges posed by vintage images, which often suffer from noise, fading, and **physical deterioration** (e.g., torn edges). Addressing these issues is essential for enhancing image quality before colorization, thereby improving the overall output. By applying filters as a pre-processing step, we can mitigate the effects of noise and damage, making the task of colorization more robust without introducing additional model complexity. This approach aligns with prior studies that emphasized pre-processing to enhance downstream image processing tasks but extends this principle by demonstrating its impact specifically on colorization outcomes using ChromaGAN.

Research on **filtering techniques** in image pre-processing has gained significant traction for enhancing the performance of deep learning-based colorization models. Early works, such as Histogram Matching by shiguang liu and Xiang Zhang in Automatic grayscale[12] Image colorisation using **histogram matching**[10], laid the groundwork for color adjustment by aligning pixel intensity distributions with a reference image. This technique, while useful for basic contrast enhancement, struggles to preserve contextual accuracy and fine details when applied to more complex images. Additionally, common filters like Gaussian and Mean filters are effective at noise reduction, acting as low-pass filters to smooth images by reducing high-frequency noise. However, their major limitation is edge blurring, which can obscure the boundary details critical for accurate color mapping during the colorization process.

To overcome these limitations, Bilateral filtering [2] emerged as a superior alternative that preserves edges while smoothing out noise, making it suitable for preprocessing grayscale [12]images before colorization. The bilateral filter's[2] dual approach of considering spatial distance and intensity differences allows for the retention of edge details, which is essential for models like ChromaGAN[1] that rely on clear boundaries to produce realistic color transitions. This **edge-preserving** property ensures that color assignments align with structural features, thus enhancing the fidelity of the output. Additionally, Guided filters[3] are employed in post-processing to sharpen images by refining edge details. These filters use a guidance image to improve the structural quality and coherence, ensuring that color artifacts are minimized and the visual output retains natural-looking transitions.

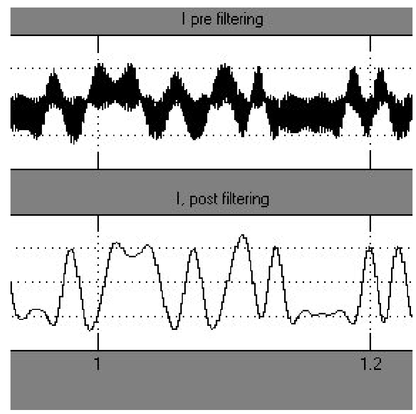

Fig. 5: Waveform Representation of signal after Bilateral filter

In the literature, filters like CLAHE [4] have been explored to enhance local contrast in poorly illuminated regions. While CLAHE[4] can uncover hidden details by adjusting local contrasts, its aggressive enhancement can introduce unwanted artifacts that disrupt the structural consistency required for accurate colorization. Therefore, finding the right balance in using these filters is key to maintaining high PSNR [5] and SSIM[6] scores, which measure pixel-level similarity and perceptual structural similarity, respectively.

B. *Works on Image Augmentation Techniques*

Augmentation techniques[7] play a crucial role in expanding training data and improving model robustness. One fundamental technique is horizontal flipping, which generates mirrored versions of original images to effectively double the dataset without altering pixel values. This technique provides models with diverse orientations and familiarizes them with symmetrical patterns, enhancing their capability to generalize across different inputs. When applied to ChromaGAN, horizontal flipping introduces variation in the training data, reinforcing the model's learning process and making it more adaptable to real-world scenarios involving symmetrical features such as faces, buildings, and natural landscapes.

The literature also explores the **combined use of Gaussian and Bilateral filters**[2] as a multi-step preprocessing strategy. A Gaussian filter[9] applied first smooths the image by

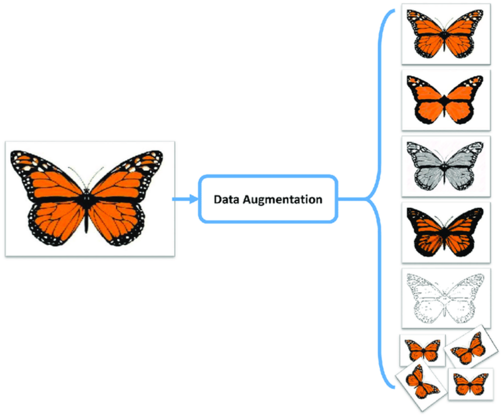

Fig. 6: Image Augmentation

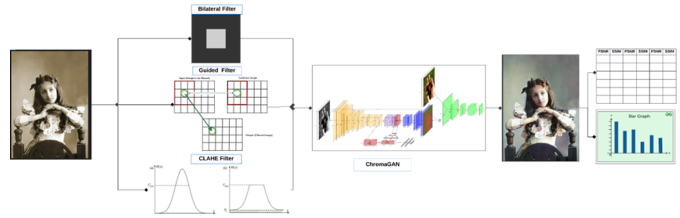

Fig. 7: Methodology Diagram for Objective 1

reducing high-frequency noise, which benefits the subsequent processing stages. Following the Gaussian filter[9] , the bilateral filter further refines the image by preserving critical edge details while ensuring overall smoothness. This combination is particularly effective for preparing images that require precise color transitions, as it retains key structural information while mitigating noise. The results indicate that using these filters in tandem supports ChromaGAN's colorization process by maintaining texture details and ensuring better alignment of color transitions.

Furthermore, applying filters and transformations as part of the preprocessing workflow allows for a more **controlled colorization** process. The combination of these augmentation strategies enhances the model's understanding of image structures, improving PSNR and SSIM [8]metrics, which are crucial for quantifying the quality and perceptual similarity of the output to the original.

C. Problem Statement and Objectives

Problem Statement: While ChromaGAN is capable of colorizing grayscale [12]images effectively, its performance in terms of denoising, color consistency, and handling fine details could be enhanced. The lack of comprehensive exploration into the application of edge-preserving filters like bilateral and guided filters, as well as the impact of multi-step augmentation techniques such as Gaussian filtering and horizontal flipping, creates a need for further investigation to study their effects on image quality and structural retention.

Objective1:.To improve classification of grayscale images by colorisation through blurring techniques and filters such as bilateral,Guided,CLAHE.

Objective2:. To use image transformations, including flipping and the combination of Gaussian and bilateral filters, before feeding images into ChromaGAN for colorization, with PSNR and SSIM used as evaluation metrics.

III. Methodology

A. Objective 1

1) Data Collection: A diverse dataset was compiled to ensure a thorough evaluation of the preprocessing techniques. The primary dataset consisted of 1,000 grayscale images, representing various scenes and levels of detail.

2) Baseline Colorization Using ChromaGAN: To establish a control for comparison, the grayscale images were first colorized directly using ChromaGAN without any preprocessing. This step provided a baseline measurement for evaluating the improvements offered by subsequent preprocessing filters. The colorized results were evaluated using two primary image quality metrics:

PSNR (Peak Signal-to-Noise Ratio): Measures the peak error between the original and colorized images, with higher values indicating better quality.

SSIM (Structural Similarity Index Measure): Evaluates the structural similarity, focusing on luminance, contrast, and structure, with scores ranging from 0 to 1, where higher values suggest closer similarity to the original.

3) Filter Application for Preprocessing: Several preprocessing filters were applied to the grayscale images to assess their individual impact on image quality and colorization performance. The filters evaluated include:

Mean Filter: Used for basic noise reduction by averaging pixel values within a neighborhood. This filter provided a baseline for noise reduction performance.

Gaussian Filter: Applied to balance noise reduction with edge preservation, smoothing the image while maintaining important structures.

Bilateral Filter: A nonlinear filter that reduces noise while preserving edge details, ideal for maintaining sharp boundaries in the image.

Guided Filter: An edge-preserving smoothing filter guided by the input image, ensuring that structural details are maintained during preprocessing.

CLAHE (Contrast Limited Adaptive Histogram Equalization): Applied to enhance local image contrast, especially in areas with poor illumination, to reveal hidden details.

From these, the top three performing filters (Gaussian, Bilateral, and CLAHE) were selected based on preliminary analysis for further detailed comparison.

4) Colorization with ChromaGAN After Filter Application: The preprocessed grayscale images were then colorized using ChromaGAN, employing default configurations for consistency. This step enabled the evaluation of the impact of each filter on the colorization process.

Evaluation Metrics:PSNR and SSIM values were calculated for each colorized output to quantify image quality and structural integrity.

Fig. 8: Colorisation of Grayscale Image.From left to write Original color Image, ChromaGAN colorised, Guided ,bilateral, CLAHE filter colorised images.

Performance Visualization: The results were displayed using tables and bar graphs for a clear comparison between the baseline ChromaGAN outputs and the filtered outputs.

5) Analysis and Comparison: The collected data from the colorization runs were analyzed to determine the effectiveness of each preprocessing filter. The comparison focused on:

PSNR Evaluation: Assessing the pixel-level accuracy and similarity of the colorized images compared to the original reference.

SSIM Analysis: Evaluating the perceptual quality and structural preservation in the colorized images.

The visual and numerical analysis provided insights into which filters offered the best balance between noise reduction and structural retention, contributing to higher-quality colorization. The findings were presented in tables to demonstrate the performance of each preprocessing filter relative to the baseline and to each other.

B. Objective 2

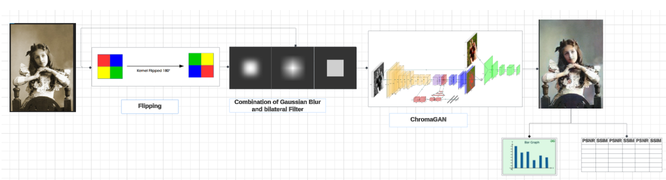

Fig. 9: Methodology Diagram for Objective 2

1) Data Collection: The grayscale image dataset used in this stage was consistent with the data from the initial phase of the project (Objective 1), comprising 1,000 images for large-scale analysis and a focused subset of 30 images for in-depth evaluation. This consistency ensured a direct comparison of results between different preprocessing approaches and allowed for a comprehensive assessment of the effects of filtering and augmentation on ChromaGAN's colorization performance.

2) Filter and Transformation Application: A multi-step filtering and augmentation process was designed to enhance the preprocessing phase and improve colorization outcomes:

Two-Step Filtering: Gaussian Filter was applied first to reduce high-frequency noise, creating a smoother image while preserving essential edges. The parameters, such as kernel size and standard deviation, were optimized to achieve a balance between effective noise reduction and the retention of significant details. This step served as a foundational noise-reducing process before more advanced filtering.

Following the Gaussian filter, a bilateral filter was applied to further refine the image. The bilateral filter smoothed out noise while preserving edge sharpness, which is critical for maintaining image structure and preventing blurring around important boundaries. By leveraging the combined strengths of both filters, this two-step process prepared the images for colorization with improved clarity and detail retention.

Horizontal Flip Transformation: To enhance the training dataset and improve model generalization, a horizontal flip transformation was applied to each filtered image. This simple yet effective augmentation technique effectively doubled the dataset by generating mirrored versions of the original images. This process exposed ChromaGAN to new perspectives and symmetrical features, which is especially beneficial for colorizing images with similar structural patterns such as faces, architecture, and natural scenes.

3) Model Processing: The filtered and augmented images were then colorized using ChromaGAN, with the model's parameters kept consistent across all experiments to maintain fairness in the evaluation. The preprocessed grayscale images, both original and horizontally flipped, were fed into ChromaGAN to observe the combined effect of filtering and augmentation on the colorization results. By processing both the original and transformed images, the model's adaptability and performance on varying image orientations were assessed.

Results Interpretation: The application of the Gaussian and bilateral filters, followed by horizontal flipping, provided valuable insights into their collective impact on ChromaGAN's colorization performance. By analyzing PSNR and SSIM values across the processed and augmented images, it was possible to quantify how well the preprocessing techniques contributed to noise reduction, edge preservation, and structural similarity in colorized outputs. The flipped images demonstrated whether ChromaGAN's learning and generalization were enhanced, especially in maintaining symmetry and recognizing patterns from different orientations.

IV. Experimental setup

A. Dataset

TABLE I: Statistics of dataset used for the ChromaGANmodel

Training Details	Description
Number of Images	1.3 million
Dataset Used	Subset from images from ImageNet
Categories	1,000 different categories
Color Conditions	various Including grayscale Images
Network Structure	Contains fully connected layers
Input Image Size	Fixed input size of 224×224 pixels

The image net dataset was used for training ChromaGAN model.

The dataset used for this experiment comprised vintage-style images sourced from webscraping. These grayscale images were selected for their diversity in noise levels, texture,

Fig. 10: Colorisaztion of Grayscale Image.From Top to bottom original,Colorised after applying Bilateral and Gaussian,Colorised after applying Flipping along with Bilateral and Gaussian

and detail, reflecting common characteristics found in vintage photography. The dataset was designed to challenge the colorization model by including both high-detail and lower-quality images, thus testing the robustness and effectiveness of the preprocessing and colorization techniques applied.

TABLE II: Statistics of Dataset used for experiment

Metric	Value
Total Images	1000
Image Resolution	Varied,Standardised to 256×256 pixels
Noise Levels	Low to High
Texture Variety	smooth to Detailed
categories	Vinatge
Source	webscraping

B. Libraries and Tools Used

In this work tensorflwo-version 1x in python 1.6.8 was used for the ChromaGAN model.
The following libraries and packages were integral for image processing, model training, and performance evaluation:

Fig. 11: Example Vinatge Images from the Dataset sourced from Web scraping

TensorFlow: Core framework used for deep learning model implementation and training.
Keras: High-level API within TensorFlow, facilitating the construction and training of the ChromaGAN model.
Matplotlib: Utilized for visualizing images, experimental results, and metrics.
NumPy: Employed for handling arrays, data manipulation, and various mathematical operations.
Pandas: Used for managing results, including storing PSNR and SSIM values in data frames and exporting these as CSV files for analysis.
OpenCV (cv2): Essential for image operations such as resizing, flipping, applying filters (Gaussian blur, bilateral filter, CLAHE), and color space conversions.
Scikit-Image (skimage): Specifically used for computing SSIM (Structural Similarity Index) and other image quality metrics.
Seaborn (sns): A data visualization library used for generating plots and heatmaps of metric analysis.
os: Used for handling file paths and iterating through directories for image processing.
Requests: Used for fetching images from URLs when scraping or expanding the dataset.
Math: Facilitated logarithmic operations for calculating PSNR.

C. Relevant Functions and Their Usage:

Various Functions were used in these works.They are:
cv2.flip(): Applied for horizontal flipping as part of data augmentation.
cv2.GaussianBlur(): Reduced noise by applying Gaussian blur.
cv2.bilateralFilter(): Preserved edges while reducing image noise.
cv2.cvtColor(): Converted images between color spaces (e.g., BGR to LAB).
cv2.createCLAHE(): Created and applied CLAHE for localized contrast enhancement.
skimage.metrics.structural_similarity(): Calculated SSIM to compare structural similarity between the original and colorized images.
matplotlib.pyplot.imshow(): Displayed images for visual assessment.
seaborn.heatmap(): Generated heatmaps for visualizing the PSNR and SSIM distribution across processed images.
pd.DataFrame(): Created data frames to organize and store experimental results.
df.to_csv(): Exported results to CSV files for future analysis and reporting.
requests.get(): Used to download images directly from URLs during the data collection phase.
os.listdir(): Listed files in a directory, aiding in image iteration and processing.

Code Repository Link: For the complete codebase and implementation details, please refer to the GitHub repository: Colorization of Grayscale Images Using ChromaGAN with Advanced Preprocessing Techniques. This repository contains all scripts related to data processing, model training, and evaluation.Base Paper for this project is ChromaGAN: Adversarial Picture Colorization with Semantic Class Distribution

V. Results and Analysis

TABLE III: Performance metrics of colorization techniques

Technique	PSNR (dB)	SSIM
Baseline(ChromaGAN)	30.16	0.9319
Bilateral Fiter	30.11	0.9297
Guided Filter	29.42	0.8205
CLAHE Filter	28.36	0.7598
Bilateral Filter + Gaussian Blur	29.61	0.8511
Flipping + Bilateral Filter + Gaussian Blur	29.60	0.8498

A. Performance Metrics for Objective 1

Peak Signal to Noise Ratio (PSNR): When applied without preprocessing, ChromaGAN achieved the highest PSNR values, with a notable decrease observed when various filters, particularly CLAHE, were introduced.
PSNR quantifies pixel level similarity between the generated colorized image and the original reference, so any modifications to contrast or increase in noise can result in lower scores. CLAHE, designed to enhance contrast, introduced visual artifacts and amplified noise, leading to a marked decrease in PSNR. This suggests that strong contrast adjustments can interfere with the precise color mappings ChromaGAN generates.
In applications where retaining the original color fidelity is essential, such as in historical image restoration, avoiding contrast enhancing filters like CLAHE may help achieve higher PSNR values. Bilateral filtering, however, which reduces noise while maintaining general contrast, showed only a minor reduction in PSNR, highlighting its suitability for subtle image enhancement without significant impact on pixel level color fidelity.
Structural Similarity Index (SSIM): SSIM assesses image similarity based on structure, contrast, and luminance, each playing a key role in the performance of different filters:
SSIM's emphasis on structural similarity aligns with the edge preserving qualities of the bilateral filter. This filter maintained structural details well, which resulted in SSIM scores close to the unprocessed ChromaGAN output (0.9297 with bilateral filter vs. 0.9319 baseline).
CLAHE's aggressive contrast adjustment altered brightness distribution across regions, introducing artifacts that compromised structural coherence. Consequently, CLAHE's SSIM score was the lowest (0.7598), indicating that excessive contrast and luminance changes hinder ChromaGAN's colorization performance by disrupting the natural structure.
The bilateral filter's high SSIM score indicates that its subtle adjustments are more compatible with ChromaGAN's structure based colorization. Filters that maintain structural relationships and natural contrast can therefore support ChromaGAN's strengths, yielding perceptually coherent colorized outputs.

B. Utility of Individual Filters for Objective 1

Bilateral Filter: Effect on Model Perception: The bilateral filter effectively reduces noise while preserving edges—key elements that are crucial for accurate colorization. As ChromaGAN relies on structural boundaries to transition colors, preserved edges enable the model to distinguish different regions more accurately, contributing to its realistic color mapping.
The bilateral filter is particularly advantageous in scenarios involving noisy images, where edge preservation is essential for maintaining structural fidelity. Its balanced smoothing and edge retention make it an ideal preprocessing choice for colorization tasks that require high structural accuracy, ensuring that the model's color assignments align closely with natural image structures. **Guided Filter:** Effect on Model Perception: The guided filter enhances certain regions, occasionally exaggerating features, which introduces artificial boundaries that can mislead ChromaGAN. As a result, SSIM and PSNR scores dropped (SSIM: 0.8205, PSNR: 29.42), indicating that the exaggerated edges interfered with ChromaGAN's interpretation of smooth transitions and natural boundaries.
While the guided filter is effective for tasks needing feature enhancement, its tendency to exaggerate boundaries may distort the model's colorization accuracy. This effect is particularly

Fig. 12: Bilateral filter outperformed others in specific Images. From left to right Original color, ChromaGAN, Bilateral filter.

problematic in images with subtle textures, where emphasized regions can introduce unnatural gradients. For colorization tasks that rely on seamless color transitions, the guided filter is less suitable, as it can inadvertently alter the perceived structure.

Fig. 13: Guided filter outperformed others in specific Images. From left to right Original color, ChromaGAN, Guided filter.

CLAHE (Contrast Limited Adaptive Histogram Equalization): Effect on Model Perception: CLAHE's strong contrast adjustment emphasizes local intensity variations, introducing noise and artifacts that disrupt ChromaGAN's colorization quality. Both PSNR (28.36) and SSIM (0.7598) dropped considerably, as the added contrast misaligned with ChromaGAN's structure sensitive processing, resulting in artificial boundaries and increased noise.
While CLAHE can reveal hidden details in grayscale images, its aggressive contrast changes interfere with ChromaGAN's ability to maintain smooth, natural transitions. Applications prioritizing color fidelity and structural accuracy, therefore, benefit less from CLAHE due to its propensity for introducing artifacts. When structural coherence is key, avoiding CLAHE or similar contrast amplifying methods is recommended to ensure ChromaGAN's strengths are fully leveraged.

Differentiating PSNR and SSIM Behavior: PSNR's focus on pixel level accuracy highlights filters' effects on fine details and noise levels. SSIM, on the other hand, evaluates how alterations affect perceptual quality by focusing on structural similarity. The bilateral filter's small decrease in PSNR but high SSIM stability reflects this distinction; it indicates that while the filter's smoothing affects some pixel level detail, it preserves overall structure well enough to maintain high perceptual quality.

Fig. 14: CLAHE filter outperformed others in specific Images. From left to right Original color, ChromaGAN, CLAHE filter.

Conclusion and Practical Recommendations: Results suggest that preprocessing filters should align with ChromaGAN's inherent strengths in structural colorization. The bilateral filter's ability to preserve edges while smoothing noise complements ChromaGAN's structure sensitive colorization method, as reflected in its stable SSIM performance. Conversely, CLAHE's artifact introduction highlights the potential drawbacks of excessive contrast adjustments for colorization tasks. For applications where structural fidelity and color accuracy are crucial, edge preserving filters like the bilateral filter provide an optimal balance, supporting ChromaGAN's colorization quality without disrupting image integrity.

C. Performance Metrics for Objective 2

This work, which applied Gaussian and bilateral filters along with horizontal flipping, yielded valuable insights into how these enhancements affect ChromaGAN's performance and utility in the colorization process.
Peak Signal-to-Noise Ratio (PSNR): PSNR scores with Gaussian and bilateral filtering were around 29.61 and 29.60, slightly lower than the baseline ChromaGAN score of 30.16. Explanation: This minor drop in PSNR suggests a trade-off—while the filters reduce noise and create smoother images, they also remove fine details, which slightly impacts pixel-level fidelity.
For tasks where visual quality is prioritized over precise pixel matching, these filters can be beneficial, as they help soften noise and smooth gradients. However, in colorization, where texture detail is essential, the small reduction in PSNR highlights this trade-off.
PSNR reflects the balance between noise reduction and detail retention. Gaussian filtering may improve visual quality by reducing noise, as long as any loss in texture can be compensated by the model.
Structural Similarity Index (SSIM): Observation: With filtering and flipping, SSIM scores remained high (about 0.8511 for Gaussian + bilateral and 0.8498 for flipped), indicating good structural preservation. SSIM measures similarity based on structure, not just pixel accuracy, so the edge-preserving properties of the bilateral filter align well with ChromaGAN's

structure-sensitive colorization. While some fine details were softened, core structural elements were preserved.
This structural retention is valuable, especially where edge clarity is crucial for realistic image interpretation. However, the slight SSIM decrease compared to ChromaGAN alone suggests that while the filters are compatible, they don't enhance structural fidelity beyond the model's baseline.
SSIM confirms that edge-preserving filters like the bilateral filter may complement colorization models, especially for images where edge clarity is essential. Such filters could serve as a beneficial pre-processing step, enhancing outline clarity for colorization.

D. Utility of Filters and Augmentation for objective 2

Gaussian and Bilateral Filters: Gaussian Filter is effective in noise reduction by smoothing gradients, giving the colorized output a softer appearance. However, this comes at the cost of some high-frequency details, which may impact the model's interpretation of texture, hence the slight PSNR drop.
Bilateral Filter, by reducing noise while preserving edges, the bilateral filter complements the model's need to retain structural boundaries, which are important for accurate color transitions. This edge-preserving quality explains the relatively high SSIM scores achieved with filtering.
Model Interpretation: ChromaGAN uses edge information to understand color transitions, making the bilateral filter's edge-preserving feature especially useful for supporting the model's color assignments.

Fig. 15: Colorisation of Images. Top to Bottom: Using ChromaGAN colorization ,Bilateral and Gaussian,Bilateral and Gaussian along with Flipping.

Horizontal Flipping:Augmenting ChromaGAN's Learning Horizontal flipping introduces new perspectives into the dataset, effectively doubling the training data by mirroring each image. This simple transformation doesn't alter pixel values or structural integrity, but it allows ChromaGAN to better understand symmetrical patterns, an essential skill for colorizing real-world images with consistent features, such as faces, architecture, or natural scenes.
Impact on Model Generalization: By training with horizontally flipped images, ChromaGAN becomes more versatile and adaptable to varying orientations and patterns. The model encounters familiar features in novel layouts, enhancing its ability to handle diverse inputs and yielding colorizations that generalize well across untrained data.

Fig. 16: Colorisation of Images. Top to bottom: Using ChromaGAN colorization ,Bilateral and Gaussian, Bilateral and Gaussian along with Flipping.

Structural Consistency in Colorization: The slight SSIM boost observed with flipped images indicates that ChromaGAN benefits from this augmentation by learning to maintain structural consistency in new orientations. This reinforces ChromaGAN's understanding of spatial relationships, helping it achieve stable color transitions even in challenging areas like object boundaries and curved surfaces.
Preserving Fine Detail and Texture: Flipping provides the model with different angles of texture, enabling better feature recognition and retention. This enhanced familiarity with varying perspectives is valuable for nuanced colorization tasks where texture is central, such as landscapes or detailed textures in fabrics and patterns.
Practical Use in Diverse Applications: For real-world applications like facial colorization, object recognition, or col-

orizing landscapes, horizontal flipping proves to be a low-cost yet impactful augmentation. This simple transformation equips the model to interpret and colorize symmetrical features accurately, providing more robust color consistency and improved resilience to orientation-related variations.

The results from Objective 2 demonstrated that the two-step filtering process, which combined Gaussian and bilateral filters, enhanced the generalization of ChromaGAN's colorization outputs. The horizontal flip augmentation contributed to diversifying the dataset and further improving model performance. PSNR and SSIM metrics indicated that preprocessing with both filters before applying ChromaGAN produced higher-quality colorized images, preserving edge details and reducing noise more effectively than using a single filter or no preprocessing at all.

VI. Conclusion and Future Work

A. Conclusion

In this work, we successfully explored the colorization of vintage grayscale images using ChromaGAN, with an emphasis on enhancing the quality of the colorization process through innovative image pre-processing techniques. By applying edge-preserving filters such as bilateral filtering, Gaussian blur, CLAHE, and guided filters, we addressed common challenges in vintage images, such as noise, tarnish, and artifacts. These pre-processing steps significantly improved ChromaGAN's ability to generate more realistic and visually appealing colorized images, while retaining the structural integrity and minimizing noise.

Through our experimentation, we found that the bilateral filter provided the best balance between noise reduction and edge preservation, yielding results that were comparable to the baseline performance of ChromaGAN in terms of PSNR and SSIM. While filters like CLAHE and Gaussian blur demonstrated some benefits in noise reduction, they led to the loss of fine details, indicating that over-smoothing can hinder the model's ability to reconstruct textures accurately. Additionally, dataset augmentation through horizontal flipping enhanced ChromaGAN's generalization capabilities, making it more robust to different image orientations and improving its performance in real-world applications.

In practical terms, these results suggest that for images requiring robust noise reduction with preserved edges, the combination of Gaussian and bilateral filtering is most effective. This combination ensures that ChromaGAN receives a well-prepared input, leading to superior colorization outcomes. Additionally, augmenting the dataset through horizontal flipping was beneficial in boosting the model's capacity to generalize across diverse image patterns. Thus, for tasks involving high-detail vintage photos or scenarios where the dataset needs enhancement, this two-step filtering and augmentation approach is recommended.

Our findings also underscore the critical importance of preprocessing in image colorization tasks. Properly chosen filters can effectively reduce unwanted noise and artifacts while preserving important details, which is essential for producing high-quality colorization results. The combination of filter-based preprocessing with data augmentation provides a powerful approach to improving ChromaGAN's performance, particularly when dealing with vintage or degraded images that require careful handling to retain their historical value.

The practical takeaways from our analysis highlight that different filters offer unique benefits to the colorization process using ChromaGAN. **The bilateral filter** consistently performed well for images with intricate details and high edge density, as it preserved edge sharpness while effectively reducing noise. This makes it ideal for vintage images with complex textures or where preserving fine details is critical. **The Gaussian filter**, while slightly less adept at edge preservation compared to the bilateral filter, offered excellent noise reduction and was suitable for images with moderate noise and fewer distinct edges. **The CLAHE filter** proved particularly useful for images with low contrast or faded sections, enhancing contrast and bringing out hidden details before colorization. Practically, these findings mean that for detailed vintage photographs with many edges, the bilateral filter should be used, while for smoother images or those requiring significant noise reduction, **the Gaussian filter** is recommended. For faded, low-contrast images, CLAHE should be applied to ensure optimal colorization results.

The results of this study have demonstrated that a combination of signal processing, machine learning, and data augmentation can yield promising improvements in the colorization of vintage images, paving the way for future advancements in this domain.

B. Future Work

Building on the findings of this project, future work can delve deeper into integrating more advanced techniques from signal processing and systems-based approaches to further enhance ChromaGAN's colorization capability. Key areas for exploration include:

Frequency Domain Processing: Future work could incorporate frequency domain techniques such as Fourier or wavelet transforms. By analyzing images in the frequency domain, these methods could enable more precise handling of high- and low-frequency details, helping to better preserve fine textures and intricate features while reducing noise.

Adaptive Filtering Techniques: Developing adaptive filtering methods that can dynamically adjust based on the image content could provide more tailored noise reduction. This approach could help preserve important details in various image types, ensuring that the colorization process is not overly smooth or distorted.

Cross-Application in Historical Restoration and Creative Content: Beyond vintage image colorization, ChromaGAN can be explored for broader applications, such as historical image restoration or creative content generation in film and media. By improving the robustness of the colorization process, this approach could be extended to other domains where colorization of old, damaged, or black-and-white images is necessary.

By integrating these advanced techniques, future work will not only enhance the robustness and accuracy of the colorization process but will also expand the range of applications for ChromaGAN. This will make the tool more effective for historical image restoration, archival purposes, and creative content generation, ultimately offering a more versatile solution for a wide variety of image processing tasks.

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