A Comprehensive Review of Illuminating and restoring Old images using Deep Learning Techniques

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ABSTRACT
The preservation and restoration of old, damaged, and black-and-white photographs pose a significant challenge due to factors such as color fading, noise, cracks, and other degradations over time. Many historical, cultural, and personal images have deteriorated, leading to a loss of visual clarity, color information, and overall image quality. Traditional image restoration methods are limited in their ability to accurately reconstruct fine details and add vibrant, realistic colors to these images. With the advancements in deep learning techniques, there is an opportunity to develop an automated system for both image colorization and image restoration. By using Generative Adversarial Networks (GANs) for colorization and Convolutional Neural Networks (CNNs) for restoration, a combined model can be proposed that achieves high-quality, visually appealing results.

Keywords
Old Image Restoration, Deep Learning, Convolutional Neural Networks (CNNs), Conditional GANs (cGANs), PatchGAN, Image Preservation.

1. INTRODUCTION
The preservation and restoration of old degraded images have become essential tasks in various fields which includes historical archiving. Recent advancements in deep learning have significantly improved these processes, employing Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) as leading techniques. CNNs are widely used for their strength in handling spatial relationships within images, making them suitable for image reconstruction and noise reduction. Meanwhile, GANs, especially Pix2Pix and conditional GANs (cGANs), have shown remarkable success in image colorization, where the model learns to predict realistic color distributions in grayscale images by training against an adversarial network. These processes are not only crucial for enhancing the visual quality of images but also for preserving the cultural and informational value embedded in historical visuals.

CNNs are particularly well-suited for image restoration due to their ability to capture spatial hierarchies and structural details effectively. By stacking convolutional layers, CNN-based restoration models can detect and correct visual degradations such as noise, blurriness, and other artifacts that typically affect old images. These networks are known for their capacity to preserve fine details within images, making them widely used in domains that require high-quality image reconstructions, including medical diagnostics, archival science, and media restoration.

GANs represent a significant advancement in image colorization. In this setup, two neural networks— the generator and the discriminator, are trained simultaneously. The generator attempts to colorize grayscale images, while the discriminator evaluates the realism of the generated images compared to true color images. This adversarial training process enables GANs to produce highly realistic and vibrant colorizations, making them particularly useful for reconstructing images that lack color data. Variants like conditional GANs (cGANs) and Pix2Pix have shown promising results in this area, allowing more control over the output by conditioning the model on specific input attributes, which is ideal for targeted colorization tasks.

The hybrid method of combining CNN and GAN architectures to leveraged the strengths of both. This hybrid approach offer an enhanced ability to address challenges in image restoration and colorization by integrating CNN-based feature extraction with the color generation capabilities of GANs. These combined methods have opened new possibilities for creating high-quality colorized versions of historically significant black-and-white images. In particular, they have paved the way for improved automatic restoration workflows, capable of

2. RELATED WORKS
A. Study of Image Colorization Using Color-Features and Adversarial Learning

H. Shafiq and B. Lee (2023) propose an advanced image colorization model using a Conditional Wasserstein GAN (CWGAN) that addresses typical colorization challenges, such as desaturation and color bleeding, through a novel Color Encoder and CBAM (Convolutional Block Attention Module) attention mechanism. The Color Encoder extracts core color features, mapping grayscale images to realistic hues while a Color Loss function ensures these generated colors align closely with ground-truth references, enhancing both vibrancy and accuracy. The PatchGAN discriminator within the CWGAN framework evaluates small patches of the image to preserve local details and spatial coherence, improving realism. Additionally, the CBAM module helps reduce color bleeding by focusing on crucial areas of the image, ensuring colors stay within intended boundaries. Despite its advancements, the model faces limitations in complex scenes where background clutter can still lead to color inconsistencies and occasional color "hallucinations." These challenges highlight the need for further refinement, especially for handling images with intricate or low-contrast areas. [1]

B. Review on Revitalizing Convolutional Network for Image Restoration

Yuning Cui, Wenqi Ren, Xiaochun Cao, and Alois Knoll (2024) introduced ConvIR, a CNN-based architecture that challenges the recent dominance of Transformer models in image restoration tasks by demonstrating comparable or superior performance with lower computational complexity. ConvIR leverages a multi-scale U-shaped design combined with a multi-shape attention module, which enhances spatial feature aggregation and reduces the impact of high-frequency artifacts. Its use of frequency modulation, integrated into a lightweight architecture, enables ConvIR to achieve robust performance across multiple tasks, including dehazing, deblurring, deraining, and desnowing. ConvIR outperforms several state-of-the-art models across 20 datasets, achieving high accuracy on complex degradations while maintaining efficiency, making it well-suited for scenarios where resources are limited. However, despite these gains, challenges remain, particularly in adapting the model to extensive datasets and in refining its handling of frequency-specific details. ConvIR's success suggests that CNN-based models, with thoughtful architectural innovations, can be viable alternatives to Transformer models, though future work is needed to address scalability and further improve performance on frequency-based tasks. [2]

C. A Study on Multi-Scale Architectures for Fast Image Restoration and Enhancement

Zamir et al. (2023) presented a novel multi-scale architecture, MIRNet-v2, for enhancing image restoration tasks such as denoising, super-resolution, deblurring, and low-light enhancement. This model addresses key challenges in image restoration, balancing the need for spatial precision and contextual information by using parallel multi-resolution convolutional streams that extract and integrate features at different scales. Through selective kernel fusion and a non-local attention mechanism, MIRNet-v2 captures both fine-grained and high-level contextual details, leading to significant improvements in image clarity and detail preservation. However, MIRNet-v2 encounters limitations with extreme noise or blur, where fine details can still be challenging to restore. [3]

D. A survey on Double-Channel Guided Generative Adversarial Network for Image Colorization

K. Du, C. Liu et al. (2021) proposed the Double-Channel Guided Generative Adversarial Network (DCGGAN), it addresses limitations in existing deep learning colorization methods, which often produce color anomalies and lose detail due to direct grayscale-to-color mapping. Traditional GAN-based colorization techniques generally map grayscale images directly to multi-channel outputs, frequently resulting in local abnormal colors and diminished structural accuracy. DCGGAN innovatively mitigates these issues by introducing two specialized modules: a Reference Component Matching Module, which automatically selects optimal reference color components for accurate color guidance, and a Double-Channel Guided Colorization Module that separately processes each color channel, reducing mapping complexity and enhancing color fidelity. The model's double-channel structure also allows it to handle diverse image types, from landscapes to character images, with reduced color inconsistency and improved overall quality. Experimental results on datasets like Google Landmarks and MegaFace demonstrate DCGGAN's superior performance across multiple quality metrics, including SSIM, PSNR, SF, and NCC, compared to baseline GANs such as CGAN and WGAN. Despite these gains, challenges remain in achieving uniform color distribution and target-specific color accuracy, particularly for varied landscapes and complex scenes. [4]

E. Survey on Transformer-Enhanced GANs for High-Quality Image Colorization

Shafiq and Lee et al. (2024) introduced an image colorization method that leverages a color transformer and GANs to address common limitations in previous colorization models, such as desaturation and color bleeding. This approach incorporates a color encoder, which uses a random normal distribution to generate color features, combined with grayscale image features in a Swin Transformer to improve color consistency and contextual relevance. The model employs a PatchGAN discriminator that evaluates image patches for local detail and texture fidelity, resulting in more coherent and visually appealing colorizations. While this model effectively captures both global and local features for high-quality output, it faces challenges in extremely complex scenes where object clutter can still lead to color inaccuracies. [5]

F. Rethinking CNN-Based Pansharpening Guided Colorization of Panchromatic Images via GANs

F. Ozcelik et al. (2021) introduces PanColorGAN, a novel GAN-based approach that reinterprets CNN-based pansharpening as a colorization task, differing from traditional methods that primarily utilize super-resolution techniques. This approach addresses the limitations observed in standard CNN-based methods, such as spatial-detail loss and blurring artifacts, by treating pansharpening as a self-supervised colorization task rather than upsampling. The model incorporates two innovative techniques: a grayscale transformation of the multispectral image to maintain spatial details and a noise injection mechanism with variable downsampling ratios to enhance generalizability across resolutions. By adopting a guided colorization framework, PanColorGAN demonstrates improved quantitative and qualitative results across multiple benchmarks, surpassing conventional CNN-based and traditional pansharpening methods in preserving both spatial and spectral fidelity. Despite its success, the model faces challenges in fully balancing spatial and spectral properties in varied image types, suggesting potential areas for future research in adaptive GAN architectures for high-resolution satellite image.[6]

G. A Survey on Self-Supervised Learning for Visual Feature Extraction via GAN-Based Colorization

Treneska, Sandra, Eftim Zdravevski et al. (2022) explored using Generative Adversarial Networks (GANs) to colorize images, leveraging this as a self-supervised method for learning visual features that can be transferred to other tasks. The authors propose a conditional GAN (cGAN) model tailored for image colorization, showing that it can generate visually realistic colors without requiring labeled data. This method successfully enhances subsequent performance in multilabel image classification and semantic segmentation when applied through transfer learning. Notably, the authors find that the features learned from this colorization model improve classification accuracy by about 5% and segmentation performance by 2.5% on standard benchmarks. However, challenges persist, such as the computational demand of GAN training and the difficulty of achieving consistently high colorization accuracy across diverse image domains. The paper suggests that future work could focus on optimizing GAN architectures for greater efficiency and exploring more complex pretext tasks to expand self-supervised learning potential in visual understanding tasks. [7]

H. Review of GAN-Based Image Restoration Method for Imaging Logging Images

Maojun Cao, Hao Feng and Hong Xiao (2023) developed a GAN-based approach to restore micro-resistivity imaging log images that suffer from partial data loss. The method integrates depth-separable convolutional residual blocks and an Inception module within a fully convolutional network (FCN) generator architecture. These components enhance multi-scale feature extraction and preserve semantic structure. Additionally, channel attention and spatial attention mechanisms are introduced to improve focus on critical image regions. For discrimination, both global and local discriminative networks ensure structural coherence across the image, producing high-quality restoration with significant textural fidelity. Experimental results demonstrate an improvement of approximately 0.3 in structural similarity (SSIM) by the proposed model compared to existing methods. However, limitations include increased computational complexity due to the added attention mechanisms, and it may struggle with extremely large missing regions, which could reduce restoration quality [8]

I. Study on Auto-Colorization of Historical Images Using Deep CNNs

Madhab Raj Joshi , Lewis Nkenyereye, Gyanendra Prasad Joshi et al. (2020) presented a CNN-based approach for colorizing historical grayscale images of Nepal. The proposed model combines a standard deep CNN with the Inception-ResNetV2 architecture to enhance both local and global feature extraction, improving the colorization's semantic quality. Using a custom dataset of 1,200 heritage images, the model predicts chroma values in the CIE Lab* color space, achieving an average PSNR of 34.65 dB and model accuracy of 75.23%. Despite these successes, the model faced challenges with specific cultural artifacts and high-resolution images due to limited data diversity and computational resources, suggesting future improvements through GAN integration and expanded training datasets. [9]

J. A comparative review of Black and White Image Colourisation using Deep Learning Techniques

F. Muscat and T. Gatt (2023) explore black-and-white image colorization through deep learning models, specifically auto-encoders and Generative Adversarial Networks (GANs). The study evaluates colorization quality using quantitative metrics like Mean Squared Error (MSE), Structural Similarity Index (SSIM), and Peak Signal-to-Noise Ratio (PSNR), complemented by a qualitative user assessment. Results indicate that while the auto-encoder model performs consistently with lower training complexity, GAN-based approaches yield higher SSIM scores, indicating better structural similarity, albeit with increased computational cost and variability in image quality. Challenges remain in colorizing complex scenes, and the study suggests a potential future for hybrid models that integrate the advantages of both auto-encoder and GAN architectures.[10]

3. INSIGHTS FROM LITERATURE AND EXISTING CHALLENGES

Recent advancements in deep learning have enabled significant progress in image restoration, particularly in tasks such as denoising, deblurring, colorization, and enhancement. Traditional methods, though foundational, often struggle with complex degradations, whereas Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) have demonstrated enhanced capabilities. Convolutional Neural Networks (CNNs) have proven effective in restoration tasks due to their ability to capture spatial hierarchies and extract detailed structural features. Multi-scale architectures within CNNs leverage parallel convolutional streams, allowing for the simultaneous capture of fine and high-level contextual details, which improves clarity and structural fidelity in restored images. Further architectural innovations, such as U-shaped designs combined with attention mechanisms, help CNNs deliver high-quality results comparable to more complex models while maintaining computational efficiency. Generative Adversarial Networks (GANs) are widely utilized in colorization tasks, where adversarial training between generator and discriminator networks yields realistic color outputs. Variants like PatchGANs and color transformer-enhanced GANs focus on maintaining color consistency and detail accuracy, effectively minimizing issues like color bleeding and desaturation seen in earlier models. Double-channel guided GANs further improve the fidelity of colorized images by separating the processing of each color channel, which reduces common mapping errors and enhances detail retention across various image types. The integration of CNNs with GAN-based frameworks has emerged as a promising approach, blending the spatial processing strengths of CNNs with the vivid color generation capabilities of GANs. Techniques such as PatchGAN, applied to historical image restoration, have shown that hybrid approaches can achieve high-quality restorations suitable for large-scale archival projects. These integrated methods contribute to automated workflows that support both historical preservation and digital media applications, opening new avenues for colorizing and restoring deteriorated black-and-white images with precision.

Despite remarkable advancements, several challenges continue to limit the full potential of deep learning-based image restoration and colorization. Key areas for improvement include computational efficiency, color consistency, data diversity, and handling extreme degradations. Many advanced deep learning models, particularly GANs with attention mechanisms, require significant computational power. The added complexity, while beneficial for detail accuracy, limits scalability and makes deploying such models challenging in resource-limited settings. Achieving uniform color distribution and high fidelity across complex scenes remains a challenge, even for advanced GAN architectures. Although guided colorization frameworks improve spatial and spectral detail preservation, balancing these elements can be difficult, especially in images with intricate or varied landscapes. Residual color artifacts and occasional inaccuracies still affect the visual quality of outputs. Model performance often declines when applied to images outside the specific types or features represented in the training dataset. Ensuring diverse and extensive datasets is critical to improving the adaptability of these models, especially for high-resolution or culturally unique images, where a lack of diversity can lead to diminished performance. Severe noise, blur, and large missing regions in images pose significant obstacles for current restoration models. While multi-resolution convolutional streams and attention mechanisms attempt to address these, further advancements are needed to improve restoration quality in highly degraded image.

4. COMPARATIVE STUDY

Table 1. Comparative analysis of image restoration and colorization models

Model	Methodology	Advantages	Limitations
Color Transformer + GAN	Utilizes a color transformer with GANs and PatchGAN discriminator to improve color accuracy and consistency.	Reduces color desaturation and bleeding; captures local and global details for high-quality colorization.	Struggles with highly cluttered scenes, where object complexity can lead to color inaccuracies.
MIRNet-v2	Employs a multi-scale CNN architecture with selective kernel fusion and non-local attention mechanisms.	Achieves detailed restoration in tasks like denoising and super-resolution; balances spatial precision.	Has difficulty with extreme noise or blur, where some fine details may still be lost.
Double-Channel Guided GAN (DCGGAN)	Introduces dual-channel processing to separately handle color channels, reducing mapping complexity.	Enhances color fidelity and reduces anomalies, suitable for diverse images (landscapes, characters).	Struggles with uniform color distribution, especially in complex natural scenes.
ConvIR	CNN-based model with multi-shape attention and frequency modulation to enhance restoration in dehazing, deblurring, and similar tasks.	High accuracy and efficiency, even with limited resources; reduces artifacts effectively.	Limited scalability on very large datasets and still needs improvement for frequency-based details in some images.
PanColorGAN	GAN-based guided colorization method for pansharpening; treats pansharpening as a colorization task.	Preserves spatial and spectral details better than standard methods; suitable for satellite imagery.	Balancing spatial and spectral properties in diverse images remains challenging.
Self-Supervised Conditional GAN for Colorization	Uses self-supervised learning with cGANs to colorize images without labeled data, useful for transfer learning.	Improves subsequent performance in classification and segmentation; effective in feature learning.	High computational cost and variability in color accuracy across different image domains.
CNN + Inception-ResNetV2 for Historical Image Colorization	Combines CNN with Inception-ResNetV2 to enhance feature extraction in colorizing grayscale heritage images.	High color accuracy and improved semantic quality; suitable for smaller historical datasets.	Limited by dataset diversity; struggles with high-resolution images and cultural-specific artifacts due to data limits.

5. CONCLUSION

In conclusion, deep learning has brought about significant improvements in restoring and colorizing old and damaged images, enabling the preservation of valuable cultural and historical data. Techniques using CNNs and GANs have shown promising results in enhancing image quality, with CNNs excelling in structural detail restoration and GANs generating realistic colorizations. When combined, these methods further improve the quality and adaptability of image restoration, making it possible to work with a variety of image types and conditions. Despite these advances, challenges remain. Current methods require substantial computational resources and often struggle with color consistency, especially in images with complex scenes. Moreover, many models rely on highly specific datasets, which can limit their effectiveness on diverse images. Extreme cases of damage, such as severe noise or large missing sections, also continue to pose difficulties for restoration models. To address these issues, future solutions and research should aim to address these challenges by developing more efficient and adaptable models. By expanding datasets, enhancing model architectures, and optimizing computational demands, future efforts can make these technologies more accessible and applicable across a broader range of image restoration needs. This progression in image restoration technology not only aids in preserving heritage images but also benefits various fields, from media to historical research.

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