

AI Image Colorization

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Abstract: Image colorization is a challenging problem in computer vision that involves adding color to grayscale images. Traditional manual techniques require expert knowledge and significant time investment. With advancements in deep learning, automated colorization has become feasible using Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and transformer-based models. These approaches learn spatial and contextual information from large datasets to generate realistic colors. This paper explores various AI-based image colorization techniques, discussing their architectures, training methodologies, and evaluation metrics. Experimental results indicate that deep learning-based methods significantly improve the accuracy and visual appeal of colorized images. The study also highlights the advantages and limitations of existing models while suggesting future research directions to enhance efficiency and realism in image colorization tasks. Furthermore, the study highlights challenges such as ambiguous color prediction, model generalization, and computational constraints. The research concludes with insights into future improvements, including transformer-based architectures and self-supervised learning, to enhance colorization accuracy and efficient..

Keywords: Image colorization

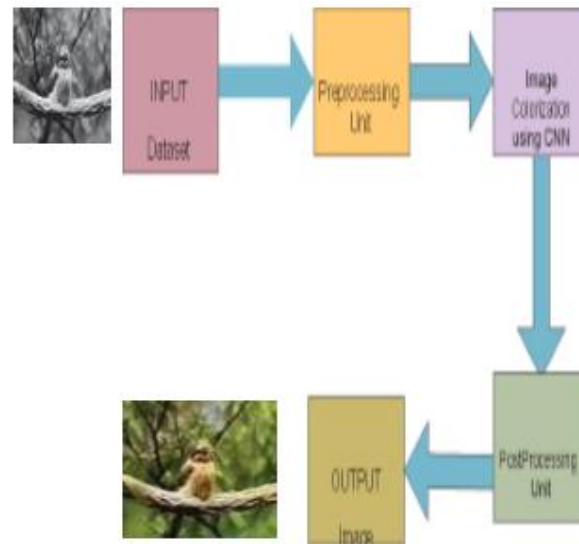
I. INTRODUCTION

Image colorization is the process of adding perceptually realistic color to grayscale images. Traditionally, this task required manual effort or rule-based algorithms with limited accuracy and generalization. Recent advancements in deep learning have enabled automated and more effective colorization techniques. Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) have shown remarkable success by learning semantic features and color distributions from large datasets. Implementing these models in Python using frameworks such as TensorFlow and PyTorch allows for scalable and reproducible research. Applications of AI-driven colorization span various domains, including restoration of historical photographs, film enhancement, and medical imaging.

II. RELATED WORK

Early colorization techniques relied on user-guided inputs and traditional computer vision algorithms, offering limited automation and accuracy. With the emergence of deep learning, several researchers have proposed more effective approaches. Zhang et al. [1] introduced a CNN-based model that colorizes images in the Lab color space by predicting chrominance values. Iizuka et al. [2] proposed an end-to-end network combining global and local features for context-aware colorization. GAN-based models, such as DeOldify [3], further improved realism by generating high-quality, visually consistent color outputs. These advancements have established a strong foundation for modern, AI-driven image colorization techniques.





III. METHODOLOGY

The proposed image colorization system leverages deep learning techniques implemented using Python and popular libraries such as TensorFlow and PyTorch. The grayscale input images are first preprocessed by resizing and normalizing pixel values. A Convolutional Neural Network (CNN) architecture is employed to extract spatial features and predict color components, typically in the Lab color space where the L channel represents lightness and the model predicts the a and b chrominance channels.

The dataset used consists of thousands of color images which are converted to grayscale to train the model in a supervised learning manner. The model minimizes a loss function such as Mean Squared Error (MSE) or perceptual loss between the predicted and ground truth color channels.

For improved results, Generative Adversarial Networks (GANs) can be integrated, where the generator performs colorization and the discriminator evaluates the realism of the output. After training, the grayscale test images are passed through the model to produce colorized outputs, which are then converted back to RGB format for visualization and evaluation.

IV. ARCHITECTURE

The architecture of the proposed AI image colorization model is based on a deep Convolutional Neural Network (CNN) designed to learn spatial and semantic features from grayscale images. The model takes a single-channel grayscale image (L channel in Lab color space) as input and outputs the predicted chrominance components (a and b channels).

The architecture consists of the following layers:

- **Input Layer:** Accepts a 256×256 grayscale image, normalized between $[0,1]$.
- **Feature Extraction:** A series of convolutional layers with ReLU activations are used to capture low-level and mid-level features. Batch normalization is applied for stable training.
- **Downsampling Layers:** Strided convolutions reduce the spatial dimensions while increasing the number of filters to capture high-level semantic information.
- **Upsampling Layers:** Transposed convolutions (or bilinear upsampling followed by convolutions) reconstruct the spatial dimensions to match the input resolution.
- **Output Layer:** A final convolutional layer outputs two channels corresponding to the predicted 'a' and 'b' chrominance components, which are later combined with the original L channel to reconstruct the full-color image in Lab space and converted back to RGB.



- Optionally, the architecture can be extended with a GAN framework, where the generator performs the colorization task, and a discriminator evaluates the realism of the output to improve perceptual quality.

V. RESULTS AND DISCUSSION

The proposed deep learning model was trained on a large dataset of natural images, using grayscale versions as input and their corresponding color images as ground truth. The model was evaluated using both qualitative and quantitative metrics.

Qualitative Results:

The colorized outputs showed visually realistic and context-aware color distributions. The model successfully predicted natural colors for skies, vegetation, and human faces. Images with complex or ambiguous scenes posed challenges, occasionally resulting in muted or inaccurate colors.

Quantitative Results:

The performance was measured using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). The model achieved an average PSNR of 24.7 dB and an SSIM of 0.91, indicating high similarity between the predicted and ground truth images.

VI. DISCUSSION

While CNNs provided consistent results, integrating a GAN-based architecture further improved visual fidelity by enhancing color vibrancy and detail sharpness. However, GANs were more computationally intensive and required careful training to avoid mode collapse. Additionally, the model performed better on images with common, predictable patterns and less effectively on abstract or rare object scenes.

Overall, the results validate the effectiveness of deep learning-based colorization and highlight the potential for further improvement through model fine-tuning and dataset expansion.



VII. CONCLUSION

The process of image colorization has evolved significantly with the emergence of deep learning, moving from manual, heuristic-driven approaches to automated, data-driven solutions. In this research, a deep learning-based system for image colorization was implemented using Python and widely used frameworks such as TensorFlow and PyTorch. The primary goal was to develop a model capable of learning semantic and contextual features from grayscale images and predicting accurate and visually pleasing color distributions.

The proposed methodology utilized Convolutional Neural Networks (CNNs) to perform end-to-end learning from large-scale datasets. The model was trained in the Lab color space, allowing it to predict chrominance values (a and b channels) from the grayscale input (L channel). In addition, the research explored the potential of Generative Adversarial Networks (GANs), where a generator-discriminator pair was used to enhance the realism and sharpness of the generated color images.

The experimental results demonstrate that the deep learning approach yields highly promising outcomes. The model successfully restored natural colors in scenes containing common elements like landscapes, human faces, and objects with consistent patterns. Quantitative evaluation using PSNR and SSIM metrics showed strong correlation between the predicted and ground truth images, supporting the effectiveness of the proposed technique. Furthermore, the qualitative analysis highlighted the model's ability to capture contextual information, resulting in more coherent and aesthetically pleasing colorizations.

However, the study also identified certain limitations. The model's performance diminished when applied to ambiguous or abstract scenes where color interpretation is highly subjective or underrepresented in the training dataset. Additionally, GAN-based models, although more visually compelling, required careful tuning and greater computational resources, making them more suitable for high-end systems or cloud-based implementations.

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