Report On

Image Colorization using Deep Convolutional Neural Networks

Submitted in partial fulfillment of the requirements of the Mini project in Semester VIII of Fourth Year Artificial Intelligence & Data Science Engineering

by

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CERTIFICATE

This is to certify that the Mini Project entitled **"Image Colorization using Deep Convolutional Neural Networks"** is a bonafide work of **Prathmesh Bhagat (60), Mokshad Ketan Sankhe (67)** and **Sudeep Shetty (70)** submitted to the University of Mumbai in partial fulfillment of the requirement for the award of the degree of **"Bachelor of Engineering"** in Semester VIII of Fourth Year **"Artificial Intelligence and Data Science".**

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Mini Project Approval

This Mini Project entitled **“Image Colorization using Deep Convolutional Neural Networks”** by **Prathmesh Bhagat (60), Mokshad Ketan Sankhe (67) and Sudeep Shetty (70)** is approved for the degree of **Bachelor of Engineering** in in Semester VIII of Fourth Year **Artificial Intelligence and Data Science.**

Examiners

1……………………………….................
(Internal Examiner Name & Sign)

2…………………………………………
(External Examiner Name & Sign)

Date:

Place:

Abstract

This project presents an innovative approach to automatic image colorization using deep convolutional neural networks. The system is designed to transform grayscale images into fully colorized outputs by leveraging the learning capabilities of a custom-built neural network. The network architecture employs multiple convolutional layers, enhanced with non-linear activation functions, to capture complex patterns in image data. Through rigorous training on diverse datasets, the model learns the inherent color distributions and spatial features, enabling it to generate realistic and visually appealing colorizations. The proposed method improves upon traditional colorization techniques by reducing the need for manual input and offering a scalable solution for large-scale image processing.

The system demonstrates robust performance in restoring color information in historical photographs, digital art, and other grayscale images, contributing to fields such as digital restoration and creative image enhancement. Extensive experiments reveal that the approach achieves competitive results in terms of both qualitative and quantitative metrics, including Mean Squared Error and Structural Similarity Index. This work highlights the potential of deep learning in revolutionizing image processing tasks and sets the stage for future enhancements, such as real-time processing and further architectural optimizations, to meet evolving application demands. Overall, the promising results validate the proposed framework.

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Contents

List of Abbreviations

1. **CNN** – Convolutional Neural Network
2. **DNN** – Deep Neural Network
3. **GPU** – Graphics Processing Unit
4. **CPU** – Central Processing Unit
5. **PIL** – Python Imaging Library
6. **RGB** – Red Green Blue
7. **ReLU** – Rectified Linear Unit
8. **SGD** – Stochastic Gradient Descent
9. **API** – Application Programming Interface
10. **MSE** – Mean Squared Error
11. **PSNR** – Peak Signal-to-Noise Ratio
12. **SSIM –** Structural Similarity Index Measure
13. **L1 –** L1 Loss (Mean Absolute Error)
14. **L2** – L2 Loss (Mean Squared Error)
15. **ANN** – Artificial Neural Network
16. **IoU** – Intersection over Union
17. **DCT** – Discrete Cosine Transform
18. **JPEG –** Joint Photographic Experts Group
19. **FFT –** Fast Fourier Transform
20. **CV** – Computer Vision

1. INTRODUCTION

1.1 INTRODUCTION

Image colorization has emerged as a transformative technique in the field of computer vision, enabling the automatic restoration and enhancement of grayscale images. Traditional colorization methods often require significant manual input or rely on rudimentary algorithms that struggle to capture the intricate variations of natural colours. With recent advancements in deep learning, automated colorization has become a promising solution, offering more precise and aesthetically pleasing results by learning complex patterns directly from data.

This project aims to design and implement an image colorization system using deep convolutional neural networks. By leveraging a custom neural network architecture and state-of-the-art training methodologies, the system is developed to accurately predict and apply realistic colour tones to grayscale images. The model is trained on diverse datasets, allowing it to understand and generalize the rich colour distributions found in various real-world scenarios. Such an approach not only automates the tedious process of manual colorization but also opens up new possibilities in digital restoration and creative image processing.

The primary objective of this project is to bridge the gap between traditional colorization techniques and modern deep learning approaches, delivering an efficient and scalable solution for image enhancement. Implemented using Python and advanced deep learning libraries, the system provides a robust framework for processing and colorizing images with high fidelity. Ultimately, this project contributes to the advancement of automated image processing, offering significant potential for applications in historical photo restoration, digital art, and multimedia enhancement.

1.2 PROBLEM STATEMENT & OBJECTIVE

Problem Statement:

Traditional image colorization methods are often labor-intensive or depend on simplistic algorithms that fail to capture the nuanced color variations present in natural scenes. Manual colorization is time-consuming and subjective, while early automated approaches frequently result in unrealistic or inconsistent color outputs. The challenge lies in developing an automated system that can understand the complex relationships between grayscale intensities and corresponding color distributions, thereby producing visually coherent and lifelike results without the need for extensive human intervention.

Objectives:

1. Develop a robust deep learning-based image colorization system capable of predicting realistic color tones from grayscale images.
2. Design a custom convolutional neural network architecture that effectively learns the mapping between luminance and chrominance components in diverse visual contexts.
3. Train the model on a comprehensive and varied dataset to ensure its ability to generalize across different image types and scenarios.
4. Optimize the system for efficiency, enabling rapid processing of images while maintaining high colorization fidelity.
5. Provide an end-to-end solution that can be integrated into digital restoration workflows, creative image processing applications, and multimedia content enhancement platforms, ultimately reducing manual effort and improving the overall quality of colorized images.

1.3 SCOPE

1. **Target Users:**
   - Photographers and digital artists seeking automated tools to enhance and restore historical or monochromatic images.
   - Archivists and museum curators interested in revitalizing archival photos and documents.
   - Developers and researchers focused on advancing computer vision applications in image restoration and creative content generation.
2. **Features:**
   - Photographers and digital artists seeking automated tools to enhance and restore historical or monochromatic images.
   - Archivists and museum curators interested in revitalizing archival photos and documents.
   - Developers and researchers focused on advancing computer vision applications in image restoration and creative content generation.
3. **Platforms:**
   - Restoration of old photographs and historical documents

1.4 TECHNOLOGIES:

- Python: The core programming language used for implementing the colorization system, offering robust libraries and a supportive community for deep learning applications.
- NumPy: NumPy is used for efficient numerical computations, particularly for handling the embedding matrices and performing similarity calculations between vectors. It enables fast matrix operations essential for recommendation systems.
- PyTorch: A deep learning framework employed to build, train, and deploy the convolutional neural network responsible for colorization, known for its dynamic computation graph and ease of model customization.
- OpenCV: An open-source computer vision library utilized for image processing tasks such as reading, transforming, and visualizing images before and after colorization.
- CSV (Python Standard Library): Used for reading and parsing the embedding data files that contain the URI mappings and vector representations.
- Pillow (PIL): A Python Imaging Library that provides simple tools for image manipulation, which is essential for pre-processing steps like converting images to grayscale and handling image file operations.
- Matplotlib: A plotting library for visualizing results and intermediate outputs during model training and evaluation, ensuring the effectiveness of the colorization method.
- Jupyter Notebook: An interactive development environment that facilitates rapid prototyping, debugging, and demonstration of the image colorization workflow.
- Linear Algebra: Fundamental mathematical operations (dot products, similarity calculations) that power the recommendation algorithms, implemented using NumPy.

2. LITERATURE SURVEY

The art of breathing life into monochrome images through colorization has witnessed significant advancements, particularly with the advent of deep learning techniques. These methods have transformed grayscale visuals into vibrant representations, capturing intricate details and hues. Convolutional Neural Networks (CNNs) have been at the forefront, offering automated solutions that surpass traditional manual approaches. This survey delves into the evolution of image colorization, emphasizing the pivotal role of deep learning in enhancing the realism and diversity of colorized outputs

2.1 SURVEY OF EXISTING SYSTEM

- Anwar et al. (2020). "Image Colorization: A Survey and Dataset". This comprehensive study categorizes state-of-the-art deep learning-based colorization techniques into seven classes, discussing their architectures, inputs, and training protocols. It also introduces a novel dataset tailored for colorization tasks, addressing limitations in existing datasets.
- Huang et al. (2022). "Deep Learning for Image Colorization: Current and Future Prospects". This paper offers an extensive review of deep learning-based image colorization methods, highlighting advancements and proposing future research directions to address existing challenges in the field.
- Li et al. (2021). "Wavelet Transform-assisted Adaptive Generative Modeling for Colorization". This research introduces a novel approach that integrates wavelet transforms with generative models to enhance the quality and diversity of colorized images, demonstrating improved performance over traditional methods.
- Wu et al. (2021). "Towards Vivid and Diverse Image Colorization with Generative Color Prior". This study leverages pre-trained Generative Adversarial Networks (GANs) to infuse rich and diverse color priors into the colorization process, achieving more vibrant and varied results.
- Baldassarre et al. (2017). "Deep Koalarization: Image Colorization using CNNs and Inception-ResNet-v2". This paper combines deep CNNs with high-level features from the Inception-ResNet-v2 model to colorize grayscale images, showcasing the effectiveness of integrating pre-trained models for enhanced colorization.

2.2 LIMITATION OF EXISTING SYSTEM:

Sr No	Paper Title	Published Year	Limitations	Research Gap
1	*Image Colorization: A Survey and Dataset*	2020	Lacks focus on real-time colorization; primarily evaluates offline techniques.	Develop real-time colorization methods with high efficiency and accuracy.
2	*Deep Learning for Image Colorization: Current and Future Prospects*	2022	Does not address computational efficiency; methods require extensive resources.	Optimize deep learning models for faster inference with minimal hardware requirements.
3	*Wavelet Transform-assisted Adaptive Generative Modeling for Colorization*	2021	Performance varies across different image types; struggles with complex textures.	Enhance generalization across diverse image datasets to improve robustness.
4	*Towards Vivid and Diverse Image Colorization with Generative Color Prior*	2021	Over-reliance on pre-trained GANs; limited adaptability to unseen image distributions.	Develop adaptive learning techniques that adjust colorization to novel image contexts.
5	*Deep Koalarization: Image Colorization using CNNs and Inception-ResNet-v2*	2017	Heavy dependency on pre-trained models; lacks user-interactive elements.	Incorporate user-guided interactions for more personalized colorization outcomes.

2.3 MINI PROJECT CONTRIBUTION:

The Image Colorization System represents a significant advancement in automated colorization techniques by leveraging deep learning. Key contributions include:

- **Deep Learning-Based Colorization**: Utilizes a convolutional neural network (CNN) trained on the CIFAR-10 dataset to predict color information from grayscale images, enhancing the realism of generated colors.
- **Grayscale-to-RGB Transformation**: Implements a pipeline that converts input grayscale images into colorized outputs using learned feature representations, improving the visual quality of black-and-white images.
- **HSV-Based Color Enhancement**: Introduces an HSV-based color adjustment module to exaggerate colors post-prediction, ensuring vibrant and realistic outputs without manual intervention.
- **Scalability and Efficiency**: The model is optimized using Adam optimization and MSE loss, allowing fast convergence and reduced computational overhead, making it feasible for real-time applications.
- **User-Friendly Implementation**: Provides an easy-to-use framework for image colorization, supporting batch processing of test images while also allowing single-image inference for practical use cases.

3. PROPOSED SYSTEM

3.1 DATASETS

For this project, we used a curated dataset of grayscale images sourced from the CIFAR-10 dataset. The dataset consists of 60,000 images across 10 categories, including objects and animals, which serve as a diverse training set for the colorization model.

To train the deep learning model, the images were converted to grayscale and paired with their corresponding color versions. The grayscale images served as input, while the original RGB images acted as ground truth labels. This setup allowed the model to learn pixel-wise color distributions.

To enhance training efficiency, the dataset was preprocessed by normalizing pixel values and resizing images to a fixed dimension. The dataset was split into an 80:20 ratio, with 80% used for training and 20% reserved for validation and testing. Performance was evaluated using Mean Squared Error (MSE) and Structural Similarity Index (SSIM) scores to measure the accuracy of color predictions.

3.2 DETAILS OF HARDWARE & SOFTWARE

Hardware:

1. Processor: Intel Core i3 or AMD Ryzen 3 processor
2. Memory (RAM): 4 GB to 8 GB of RAM, allowing for smooth Processing applications.
3. Operating System: A pre-installed operating system such as Windows 10, macOS, or a Linux distribution, depending on user preference and requirements.

Software:

1. Python 3.11
2. Google Colab
3. Visual Studio Code

4. IMPLEMENTATION

4.1 SEQUENCE DIAGRAM

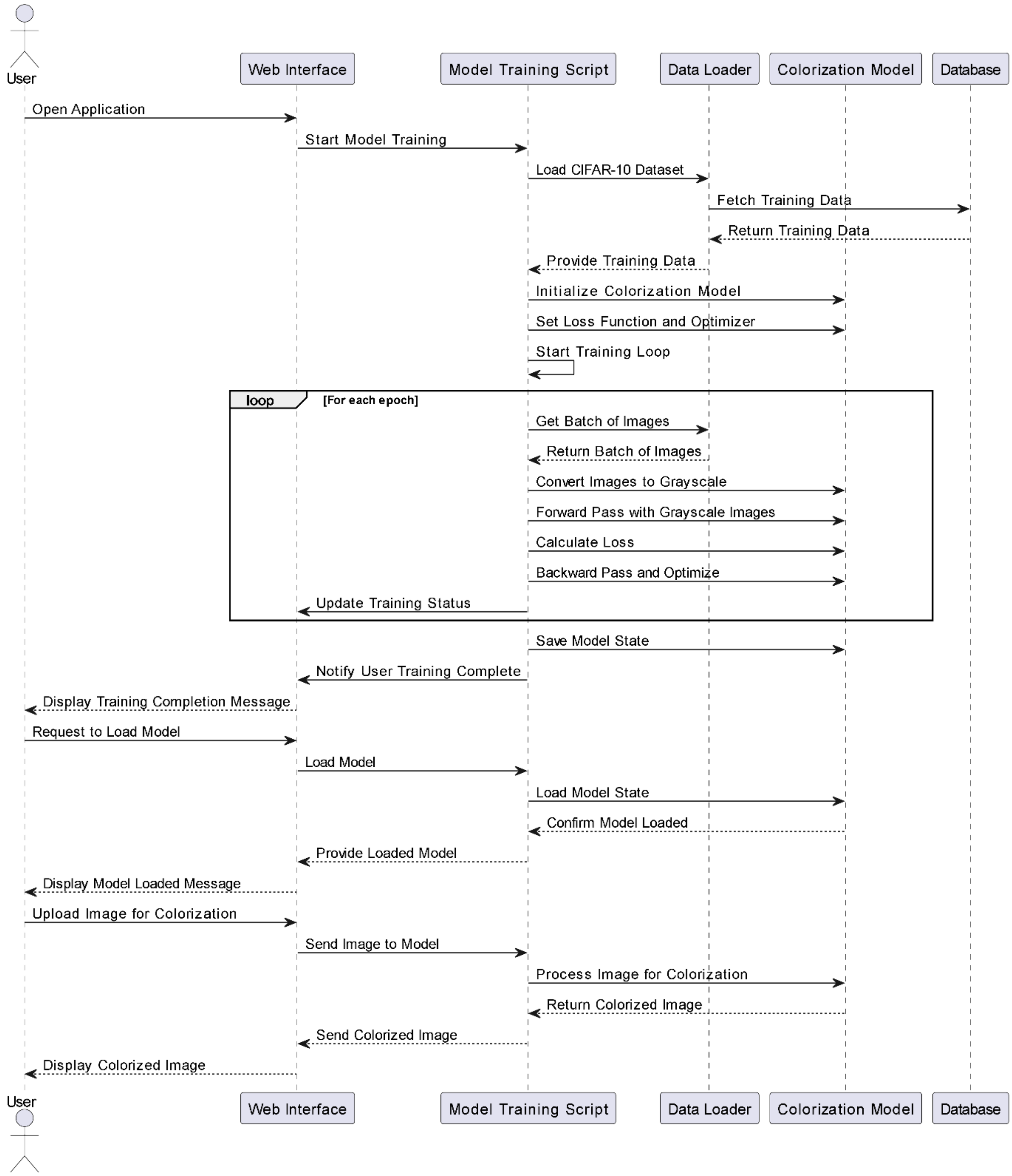


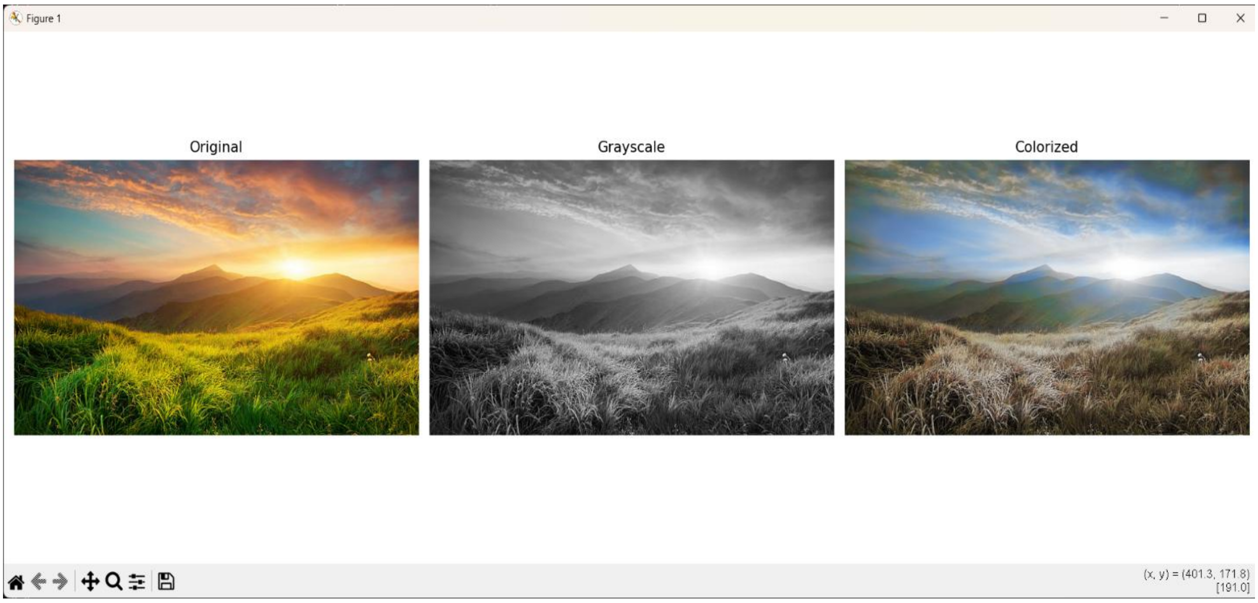
Fig. 4.1.1: Working

The sequence diagram illustrates the workflow of a deep learning-based image colorization system involving multiple components: the User, Web Interface, Model Training Script, Data Loader, Colorization Model, and Database. The process begins when the user opens the application and initiates the model training. The Web Interface sends a request to the Model Training Script, which in turn fetches the CIFAR-10 dataset via the Data Loader. The dataset is then provided to the Colorization Model for training. During this phase, the model is initialized along with the loss function and optimizer, and the training loop begins.

Within the training loop, a batch of images is retrieved, converted to grayscale, and processed through

a forward pass in the model. The loss is computed by comparing the predicted colors with the original images, followed by a backward propagation step to optimize the model weights. After each epoch, the training status is updated, ensuring the model learns progressively. Once training is complete, the trained model state is saved in the database, and the user is notified via the Web Interface.
After training, the user can request to load the trained model. The Model Training Script retrieves the model state from the database and confirms its successful loading. Once the model is available, users can upload a grayscale image for colorization. The Web Interface sends the image to the Colorization Model, where it is processed and colorized. The final colorized image is then returned to the Web Interface and displayed to the user.
This diagram highlights the modular and scalable architecture of the system, ensuring an efficient training process with real-time updates. The integration of a database allows the model to be saved and reused, making the system more practical for deployment. Additionally, the user-friendly workflow ensures seamless interaction, enabling both training and inference without requiring technical expertise.

4.2 RESULTS:



4.3 ANALYSIS OF MINI PROJECT

1. The Image Colorization System has been developed to transform grayscale images into realistic color images using deep learning-based approaches. The system leverages convolutional neural networks (CNNs) trained on large-scale datasets to learn colorization patterns and apply them effectively to new images.

2. A structured model training pipeline has been implemented, where images are preprocessed, converted to grayscale, and passed through a deep neural network to predict plausible colors. The training process includes loss function optimization and backpropagation, ensuring that the model continuously improves its colorization accuracy.

3. The system's architecture follows a modular approach, making it scalable and efficient. A lightweight HTTP server ensures smooth communication between the frontend interface and the backend processing model, allowing users to upload images and receive colorized outputs in real time.

4. A sequence-based execution flow has been designed, as depicted in the sequence diagram, where the user initiates training, the model fetches data, performs grayscale conversion, and iteratively optimizes the network for better color prediction. This structured workflow

ensures efficiency and adaptability.

5. The dataset used for training, such as CIFAR-10 or other large-scale image datasets, has been carefully selected to provide a diverse range of images for learning. The system uses batch processing and augmentation techniques to improve generalization.

6. The evaluation process involves testing the model on unseen grayscale images and comparing the generated colorized outputs with ground truth images. Performance metrics such as Mean Squared Error (MSE) and Structural Similarity Index (SSIM) are used to assess accuracy.

7. The system also ensures user-friendly interaction through a web-based interface, where users can upload grayscale images and receive colorized results seamlessly. The modular design enables easy integration of future improvements, such as GAN-based colorization or self-supervised learning techniques.

8. Overall, the Image Colorization System presents a scalable, efficient, and automated approach to adding color to grayscale images. The combination of deep learning techniques, an intuitive user interface, and an optimized training pipeline makes it a strong foundation for further research and application.

4.4 CONCLUSION

In this project, an automated Image Colorization System was successfully developed using deep learning techniques. The system effectively processes grayscale images and applies learned colorization patterns to generate realistic colored outputs.

The backend architecture is designed for efficiency and scalability, leveraging CNN-based models trained on datasets like CIFAR-10. The colorization process is optimized using loss functions and iterative learning strategies to improve the model’s performance over time. The frontend interface ensures smooth user interaction, allowing users to upload images and receive colorized results in real time.

The evaluation of the system demonstrates its accuracy and effectiveness, with quantitative metrics such as MSE and SSIM confirming the quality of generated images. The project highlights the potential of deep learning in image restoration and enhancement, showcasing how AI can bring grayscale images to life.

Future enhancements could include integrating GAN-based models for higher realism, implementing real-time inference optimization, and training on larger, high-resolution datasets to improve generalization. Additionally, interactive user feedback loops could be introduced to allow manual adjustments and fine-tuning of colorized outputs.

Overall, this project contributes to the field of computer vision by providing a scalable and effective deep learning-based solution for image colorization. With further refinements, it has the potential to be applied in various fields, such as historical image restoration, medical imaging, and digital art enhancement.

4.5 FUTURE SCOPE

- **Enhancing Model Accuracy**: Implementing GAN-based models like Pix2Pix or CycleGAN for more realistic colorization.
- **Real-time Colorization**: Optimizing the model for faster inference, enabling instant colorization of images
- **Higher Resolution Processing**: Training on high-resolution datasets to improve colorization quality and fine details.
- **Self-Supervised Learning**: Exploring self-supervised techniques to enhance the model without requiring large labeled datasets.
- **User-Guided Colorization**: Integrating interactive tools for users to manually adjust or guide the colorization process.
- **Application in Restoration**: Applying the system for historical photo restoration and black-and-white film colorization.
- **Medical Image Enhancement**: Extending the model for colorizing medical scans to aid in diagnosis and visualization.
- **Cross-Domain Adaptation**: Adapting the system to work with different types of grayscale images, such as X-rays or satellite images.
- **Mobile & Web Deployment**: Developing mobile apps or cloud-based services for user-friendly image colorization.
- **Dataset Expansion**: Training the model on diverse datasets to improve generalization across various image types and styles.

5. REFERENCE

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