IMAGE COLORISATION

A report on
Deep Learning Lab Project
[CSE-3281]

Submitted By
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Image Colorisation using U-Net and Generative Adversarial Networks

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Abstract— Image colorization is a fundamental task in computer vision, aiming to infuse grayscale images with natural-looking colors for improved visual interpretation and aesthetic appeal. In this report, we present a methodological framework for image colorization utilizing deep learning techniques, notably Generative Adversarial Networks (GANs) and the U-Net architecture. Leveraging the Coco dataset, known for its diverse and high-resolution images, our approach involves training and evaluating a GAN-based model. The model consists of a generator and discriminator network, where the generator employs a U-Net architecture for effective spatial information capture, while the discriminator distinguishes between real and synthetic colorized images. Through iterative optimization and evaluation using metrics such as adversarial losses and pixel-wise differences, we systematically assess the model's performance and refine its capabilities. The methodology encompasses crucial steps including data preparation, model training, evaluation, and optimization, providing a comprehensive approach to image colorization. Experimental results demonstrate the effectiveness of our approach in generating high-quality colorized images, showcasing the potential of deep learning techniques in computer vision applications. This report contributes valuable insights into advancing image colorization methodologies.

I. INTRODUCTION

In the realm of computer vision, image colorization stands as a significant challenge, demanding innovative solutions to achieve superior results. This project seeks to navigate this landscape by harnessing the capabilities of two state-of-the-art deep learning architectures: the U-Net and the Generative Adversarial Network (GAN). Through their strategic integration, we aim to elevate the accuracy and realism of colorized images, pushing beyond the limitations inherent in conventional methodologies. U-Net has gained prominence for its prowess in semantic segmentation tasks, excelling at pixel-level contextual understanding. However, its application in image colorization remains relatively unexplored, prompting a closer examination of the unique challenges associated with this specific domain. Concurrently, GANs have demonstrated success in generating realistic images through adversarial training. Yet, challenges such as mode collapse and training instability necessitate a careful approach when adapting GANs for image colorization. By bringing together the strengths of U-Net and GANs, this project aims to create a nuanced framework that addresses the limitations of standalone approaches, ushering in a new era of advancements in image colorization. Our project seeks to leverage the strengths of both U-Net and GANs to develop a refined framework that overcomes the shortcomings of standalone approaches. By doing so, we aim to propel advancements in image colorization, opening up new possibilities for applications in various fields.

II. LITERATURE REVIEW

Automatic Image Colorisation using Deep Learning:

In the groundbreaking exploration conducted by Pandey, Sahay, and Jayavarthini, their research on automatic image colorization using deep learning stands out as a pivotal contribution that delves into the uncharted territory of the untapped potential inherent in deep neural networks. The study not only sheds light on the transformative capabilities of these networks but also accentuates their profound impact on the evolving landscape of image processing. The researchers' approach transcends conventional methodologies, unveiling a paradigm shift in the way we perceive and execute image colorization tasks.

The study's significance extends beyond the mere presentation of promising results; it serves as a catalyst for a comprehensive examination of the intricate trade-offs between model complexity and computational efficiency. By scrutinizing these nuances, the researchers pave the way for a deeper understanding of the challenges and opportunities inherent in deploying advanced deep learning models for image colorization. This critical analysis not only contributes to refining existing techniques but also sparks contemplation on innovative approaches that strike an optimal balance between sophistication and resource efficiency.

Moreover, the study introduces a novel perspective, injecting fresh insights into the discourse surrounding the utilization of deep neural networks for image colorization. The researchers propel the field forward by highlighting the potential for groundbreaking discoveries, challenging traditional paradigms, and setting the stage for transformative breakthroughs. The exploration of this novel perspective opens avenues for future research endeavors, encouraging scholars and practitioners to explore the full spectrum of possibilities offered by deep learning in the realm of image processing.

While the results of the study are undeniably promising, the researchers wisely call for a deeper investigation into the scalability of their model concerning large datasets. This foresight is particularly relevant in the contemporary landscape, where the handling of diverse and extensive image datasets has become increasingly critical in real-world applications. This call for further inquiry points to the researchers' commitment to addressing practical challenges and ensuring the applicability of their findings in broader contexts.

Furthermore, the suggestion for an enhanced emphasis on evaluation metrics and thorough comparisons with existing methods underscores the researchers' dedication to rigorously establishing the efficacy of their proposed approach. By advocating for a more comprehensive evaluation framework, the study not only aims to validate its own contributions but also sets a precedent for future advancements in the field. Establishing a benchmark for the evaluation of image colorization techniques becomes not just a necessity but a cornerstone for fostering continuous improvement and innovation in this rapidly evolving domain.

Image Colorisation using Deep Learning:

IIn the expansive domain of image colorization utilizing deep learning, the scholarly work conducted by Mavekar, Chaudhari, Bhosale, and Dr. Sangam represents a commendable effort in providing a comprehensive perspective. Their study not only delves into the technical intricacies of the employed deep learning model but also conscientiously addresses critical considerations pertaining to dataset characteristics and preprocessing steps. This holistic approach contributes significantly to our collective understanding of the multifaceted challenges inherent in the complex task of image colorization.

The study's meticulous examination of both technical and procedural aspects serves to enrich the discourse surrounding image colorization methodologies. By dissecting the intricacies of the deep learning model's architecture and elucidating the nuances of dataset preparation, the researchers offer valuable insights that transcend mere algorithmic application. This holistic understanding is imperative for advancing the field, ensuring that future endeavors are informed by a nuanced comprehension of the interplay between model design and dataset characteristics.

However, the study, while commendable, does not shy away from acknowledging its potential limitations, including concerns related to dataset diversity and the generalization of the proposed model. This intellectual honesty sets a commendable precedent and beckons for further investigation into these aspects. A more elaborate discussion on the impact of dataset biases on colorization performance could serve as a gateway to uncovering the model's generalization capabilities across diverse real-world scenarios. By peeling back the layers of dataset intricacies, the researchers can contribute to a more robust understanding of how their proposed model might navigate the challenges posed by varied and complex datasets.

Moreover, the study wisely recognizes the importance of considering the computational resources required for training the deep learning model, addressing a crucial facet of practicality and scalability. An in-depth exploration into the intricacies of resource efficiency, particularly in large-scale applications, would provide invaluable insights. Understanding the computational demands of the proposed approach not only contributes to

the feasibility assessment but also guides future researchers in optimizing their methodologies for real-world deployment.

In essence, while the study by Mavekar, Chaudhari, Bhosale, and Dr. Sangam presents a commendable exploration into image colorization using deep learning, it serves as a springboard for further investigations. By conscientiously acknowledging its own limitations and advocating for a deeper dive into dataset biases and computational resource considerations, the study sets the stage for continuous improvement and refinement in the pursuit of effective and scalable image colorization techniques.

Image Colorisation using Generative Adversarial Networks:

The significant contribution of Nazeri, Ng, and Ebrahimi to the extensive literature on image colorization utilizing Generative Adversarial Networks (GANs) is marked by its innovative approach that introduces a paradigm shift in the domain. By leveraging the adversarial training paradigm, the authors present a methodology that not only proposes a novel way to generate realistic and visually appealing colorized images but also opens up a realm of creative possibilities facilitated by the power of adversarial training. This pioneering study not only showcases the immense potential of GANs in the context of image colorization but also sheds light on the transformative impact that adversarial training can have on pushing the boundaries of visual synthesis.

While the study admirably demonstrates the promising aspects of GAN-based colorization, it candidly acknowledges the challenges associated with training stability and mode collapse. Recognizing these challenges as crucial aspects for consideration, the authors pave the way for future advancements by signaling the need for thorough exploration and mitigation strategies. A deeper dive into the intricacies of the strategies employed to tackle mode collapse and training instability in the GAN-based colorization approach would undoubtedly yield valuable insights, enhancing the overall understanding of the proposed model's robustness in handling these inherent adversarial training challenges.

Moreover, the study wisely calls for a comparative analysis with other colorization methods, highlighting the importance of understanding the broader landscape of available techniques. Such a comparative assessment would not only contribute to a more holistic understanding of the proposed model's efficacy but also empower researchers to make informed choices in their approach to image colorization. This call for a comparative analysis fosters a necessary dialogue within the research community, encouraging discussions on the relative strengths and weaknesses of different colorization techniques and guiding the collective efforts toward the most effective and versatile solutions.

In essence, the work of Nazeri, Ng, and Ebrahimi stands as a beacon of innovation in the realm of image colorization using GANs. While celebrating the potential of adversarial training for generating compelling colorized images, the study's acknowledgment of challenges and its forward-looking recommendations for further exploration contribute to the ongoing evolution of techniques in this exciting and transformative field.

Summarizing the limitations and disadvantages of the GAN-based colorization study, it is recommended that the paper provides more insights into strategies to mitigate mode collapse and training instability. A comparative analysis with other colorization methods would enrich the study and offer a broader perspective on the proposed model's effectiveness. By addressing these aspects, the study could not only strengthen its contribution to the field but also guide future research directions, fostering a more collaborative and informed approach to image colorization using Generative Adversarial Networks.

In conclusion, the amalgamation of these studies serves as a pivotal cornerstone in shaping the dynamic and ever-evolving landscape of image colorization through the lens of deep learning. By providing in-depth insights into the methodologies harnessed, the challenges confronted, and the promising avenues for future exploration, these research endeavors collectively contribute to the maturation of this interdisciplinary field. The critical examination of these works not only elucidates the intricacies of automatic image colorization but also accentuates the delicate balance between innovation and practical implementation.

The comprehensive scrutiny of these studies not only highlights their individual contributions but also underscores the broader narrative of advancements within the realm of computer vision and deep learning. By

elucidating the intricacies of model architectures, dataset considerations, and evaluation metrics, these studies pave the way for a more nuanced understanding of the intricacies involved in the complex process of image colorization using deep learning.

III. **RESEARCH GAPS**

1. Inadequate exploration of hyperparameter tuning to mitigate GAN training instability.
2. Limited investigation into strategies for overcoming U-Net's contextual limitations in colorization tasks.

IV. **OBJECTIVES**

- Implement a model for image colorisation using Generative Adversarial Networks which utilises U-Net as the generator.
- Evaluate the models performance with a range of metrics such as loss of discriminator for fake and real images, adversarial loss of generator, and L1(MAE) loss between generated image and ground truth image.

V. **METHODOLOGY**

A. Summary

Our methodology for implementing an optimal image colorisation model is as follows.

- Data Preparation
- Building the Generator(U-Net)
- Building the Discriminator
- GAN Loss
- Training the model
- Evaluation of the model

B. Data Set

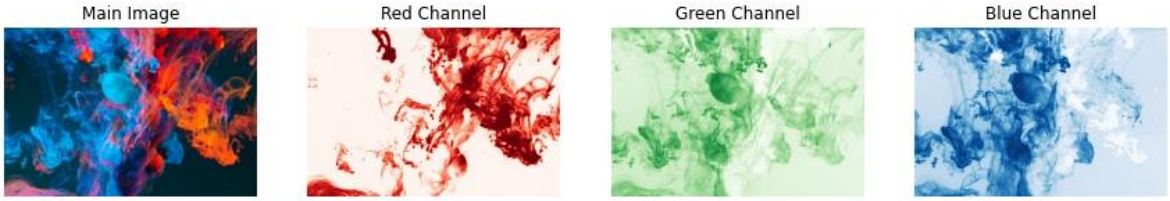
For the image colorization task, we utilize the Microsoft Common Objects in Context (COCO) dataset, a large-scale and diverse collection of images designed for object detection, segmentation, and captioning tasks. COCO comprises over 330,000 images with more than 200,000 labelled across 80 object categories, providing a rich and varied set of visual scenes that encompass a wide range of objects and scenarios. The dataset is renowned for its complexity and variety, containing images from complex everyday scenes with common objects in their natural context. This diversity makes COCO an ideal choice for training deep learning models in image colorization, as it exposes the model to a wide array of textures, contexts, and color patterns, enhancing its ability to generalize and accurately predict colors across different subjects and settings. The images in COCO are annotated with precise segmentation masks, facilitating advanced image processing and analysis tasks. However, for the purpose of colorization, we primarily leverage the raw image data, converting them into grayscale as input to train the model to predict the original colors, thus enabling the neural network to learn a wide palette of colors and their contextual associations.

C. Data Preparation

Initially, a subset of 10,000 images is randomly sampled from the COCO dataset to ensure a representative yet manageable dataset size for training and validation purposes. This subset is further divided into training and validation sets, with 80% (8,000 images) allocated for training and the remaining 20% (2,000 images) designated for validation.

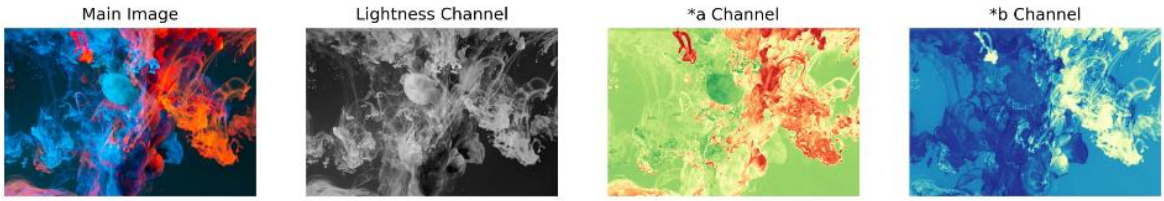
Each image undergoes preprocessing steps tailored to facilitate effective training of the deep learning model. Initially, the images are loaded and resized to a consistent dimension of 256x256 pixels using bicubic interpolation. Additionally, a random horizontal flip augmentation is applied exclusively to the training set to augment the dataset and enhance model generalization capabilities.

Figure A. RGB Color Space



Subsequently, the RGB images are converted to the Lab color space, which separates the images into the luminance ('L') channel representing grayscale information and the chrominance ('a' and 'b') channels encoding color information. The 'L' channel is normalized to the range [-1, 1], while the 'a' and 'b' channels are normalized to [-1, 1] to ensure consistent input scaling for the neural network model. Finally, the preprocessed image data is organized into batches and loaded into PyTorch dataloaders for efficient training and validation processes.

Figure B. L*a*b color space



The Lab color space, also known as CIELAB, is a color space designed to approximate human vision and perceptual uniformity. Unlike traditional color spaces like RGB and CMYK, Lab separates color information into three channels: lightness ('L') and two color opponent axes ('a' and 'b'). The 'L' channel represents the luminance or brightness of the image and is independent of color. The 'a' and 'b' channels, on the other hand, encode color information. The 'a' axis ranges from green to red, with negative values representing green and positive values indicating red. The 'b' axis ranges from blue to yellow, with negative values representing blue and positive values indicating yellow. Lab color space has several advantages, including perceptual uniformity, which means that a change of the same amount in the Lab space results in a consistent perceptual change across different colors. This property makes Lab particularly suitable for color-related tasks such as image processing, color correction, and colorization. In the context of image colorization, Lab facilitates the separation of grayscale ('L') and color ('a' and 'b') information, enabling neural networks to predict color based on grayscale input effectively.

This data preparation pipeline ensures that the input data is appropriately formatted and augmented to facilitate effective training of the image colorization model on the COCO dataset.

D. Building the Generator(U-Net Block)

In our endeavor to construct a potent image colorization model, we employ a U-Net architecture to serve as the generator within our Generative Adversarial Network (GAN). The U-Net, a renowned architecture in the realm of computer vision, is adept at handling image-to-image translation tasks. Our implementation of the U-Net is characterized by its intricate design, which encompasses both down-sampling and up-sampling modules to facilitate effective feature extraction and reconstruction.

```python
class UnetBlock(nn.Module):
    def __init__(self, nf, ni, submodule=None, input_c=None, dropout=False,
                 innermost=False, outermost=False):
        super().__init__()
        self.outermost = outermost
        if input_c is None: input_c = nf
        downconv = nn.Conv2d(input_c, ni, kernel_size=4,
                             stride=2, padding=1, bias=False)
        downrelu = nn.LeakyReLU(0.2, True)
        downnorm = nn.BatchNorm2d(ni)
        uprelu = nn.ReLU(True)
        upnorm = nn.BatchNorm2d(nf)

        if outermost:
            upconv = nn.ConvTranspose2d(ni * 2, nf, kernel_size=4,
                                        stride=2, padding=1)
            down = [downconv]
            up = [uprelu, upconv, nn.Tanh()]
            model = down + [submodule] + up
        elif innermost:
            upconv = nn.ConvTranspose2d(ni, nf, kernel_size=4,
                                        stride=2, padding=1, bias=False)
            down = [downrelu, downconv]
            up = [uprelu, upconv, upnorm]
            model = down + up
        else:
            upconv = nn.ConvTranspose2d(ni * 2, nf, kernel_size=4,
                                        stride=2, padding=1, bias=False)
            down = [downrelu, downconv, downnorm]
            up = [uprelu, upconv, upnorm]
            if dropout: up += [nn.Dropout(0.5)]
            model = down + [submodule] + up
        self.model = nn.Sequential(*model)

    def forward(self, x):
        if self.outermost:
            return self.model(x)
        else:
            return torch.cat([x, self.model(x)], 1)

class Unet(nn.Module):
    def __init__(self, input_c=1, output_c=2, n_down=8, num_filters=64):
        super().__init__()
        unet_block = UnetBlock(num_filters * 8, num_filters * 8, innermost=True)
        for _ in range(n_down - 5):
            unet_block = UnetBlock(num_filters * 8, num_filters * 8, submodule=unet_block, dropout=True)
        out_filters = num_filters * 8
        for _ in range(3):
            unet_block = UnetBlock(out_filters // 2, out_filters, submodule=unet_block)
            out_filters //= 2
        self.model = UnetBlock(output_c, out_filters, input_c=input_c, submodule=unet_block, outermost=True)

    def forward(self, x):
        return self.model(x)
```

Figure C. U-Net Code Snippet

The code snippet presented orchestrates the construction of the U-Net in a systematic manner. Starting from the middle section of the U shape, corresponding to the core of the architecture, the code progressively adds down-sampling and up-sampling modules at each iteration until it encompasses the entire U-Net structure. This iterative process results in a hierarchical architecture capable of capturing both global context and fine-grained details essential for accurate image colorization.

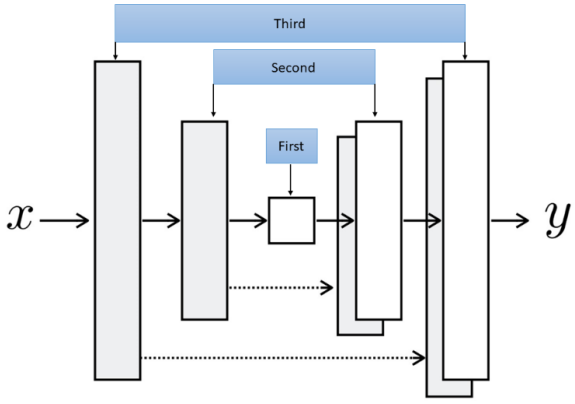


Figure D. U-Net Block

As depicted in the accompanying image, the blue rectangles illustrate the sequential assembly of the U-Net's constituent modules. While the depicted U-Net encompasses a simplified representation of the architecture, it effectively conveys the essence of the code's operation. Notably, the code specifies the depth of the U-Net, indicating the number of layers traversed during the down-sampling phase, ultimately culminating in a compact representation before undergoing up-sampling to reconstruct the output image.

With the U-Net architecture fully constructed, the code snippet paves the way for immersive experimentation and exploration. Its modularity and flexibility empower researchers to delve into the nuances of image colorization, offering a playground for tinkering with various architectural configurations and training strategies.

Through hands-on engagement with the code, researchers can gain a deeper understanding of the intricacies involved in image-to-image translation tasks.

In conclusion, the U-Net generator plays a pivotal role in our image colorization pipeline, embodying a fusion of architectural sophistication and practical utility. Its implementation, guided by the presented code snippet, underscores the transformative potential of deep learning architectures in the realm of computer vision. As we embark on our journey towards vibrant and lifelike image colorization, the U-Net generator stands as a beacon of innovation and exploration, beckoning researchers to unlock new frontiers in visual enhancement.

E. Building the Discriminator

The architecture of our discriminator is straightforward yet effective. This code snippet constructs a discriminative model by stacking Convolutional-Batch Normalization-LeakyReLU blocks, designed to discern the authenticity of input images. Notably, the discriminator's design avoids normalization and activation functions in the first and last blocks, respectively, with the final block's activation implicitly embedded within the subsequent loss function.

```
class PatchDiscriminator(nn.Module):
    def __init__(self, input_c, num_filters=64, n_down=3):
        super().__init__()
        model = [self.get_layers(input_c, num_filters, norm=False)]
        model += [self.get_layers(num_filters * 2 ** i, num_filters * 2 ** (i + 1), s=1 if i == (n_down-1) else 2)
                          for i in range(n_down)]

        model += [self.get_layers(num_filters * 2 ** n_down, 1, s=1, norm=False, act=False)]

        self.model = nn.Sequential(*model)

    def get_layers(self, ni, nf, k=4, s=2, p=1, norm=True, act=True):
        layers = [nn.Conv2d(ni, nf, k, s, p, bias=not norm)]
        if norm: layers += [nn.BatchNorm2d(nf)]
        if act: layers += [nn.LeakyReLU(0.2, True)]
        return nn.Sequential(*layers)

    def forward(self, x):
        return self.model(x)
```

Figure E. Discriminator Code Snippet

A notable feature of our discriminator is its classification strategy, known as a "Patch" Discriminator. Unlike conventional discriminators that output a single scalar representing the authenticity of the entire image, a patch discriminator divides the input image into smaller patches, typically around 70 by 70 pixels, and evaluates the authenticity of each patch individually. This localized approach allows the discriminator to discern subtle nuances and local changes essential for the task of image colorization. In our implementation, the discriminator's output shape is 30 by 30, indicative of the decision made for each patch, although the actual patch size is computed based on the receptive field of these output values.

The rationale behind employing a patch discriminator for image colorization lies in its ability to capture intricate details and local variations inherent in the colorization process. By evaluating patches individually, the discriminator can effectively discern subtle color shifts and nuances, thus enhancing the fidelity and realism of the colorized output. This localized approach aligns with the nuanced nature of colorization tasks, where precise adjustments at the local level are crucial for achieving high-quality results.

In essence, the patch discriminator serves as a fundamental component in our image colorization pipeline, embodying a balance of simplicity and effectiveness. Its localized classification strategy and tailored design underscore its suitability for discerning subtle color variations, thereby facilitating the generation of vibrant and lifelike colorized images. As we delve deeper into image colorization, the patch discriminator remains pivotal in advancing the capabilities of computer vision algorithms.

F. GAN Loss

This code snippet below defines a fundamental element of our colorization model: the calculation of the GAN loss. In the context of Generative Adversarial Networks (GANs), the GAN loss is crucial for training as it drives the adversarial learning process between the generator and discriminator networks.

```
class GANLoss(nn.Module):
    def __init__(self, gan_mode='vanilla', real_label=1.0, fake_label=0.0):
        super().__init__()
        self.register_buffer('real_label', torch.tensor(real_label))
        self.register_buffer('fake_label', torch.tensor(fake_label))
        if gan_mode == 'vanilla':
            self.loss = nn.BCEWithLogitsLoss()
        elif gan_mode == 'lsgan':
            self.loss = nn.MSELoss()

    def get_labels(self, preds, target_is_real):
        if target_is_real:
            labels = self.real_label
        else:
            labels = self.fake_label
        return labels.expand_as(preds)

    def __call__(self, preds, target_is_real):
        labels = self.get_labels(preds, target_is_real)
        loss = self.loss(preds, labels)
        return loss
```

Figure F. GAN Loss Code Snippet

Within the `GANLoss` class, the choice between different GAN loss functions, namely "vanilla" and "lsgan," is determined during initialization. The "vanilla" mode typically utilizes Binary Cross Entropy with Logits Loss, while the "lsgan" mode employs Mean Squared Error Loss. These options provide flexibility for optimizing the model's performance based on specific training requirements.

Additionally, the `get_labels` method generates appropriate labels for the discriminator's predictions, guiding it to distinguish between real and fake samples accurately. By incorporating constant tensors as the "real" and "fake" labels, this class ensures consistency and efficiency in label generation across training iterations.

Beyond the technical details, understanding the role of the GAN loss in our colorization model is essential. As our model endeavors to generate realistic colorized images from grayscale inputs, the GAN loss guides the generator network to produce colorizations that closely resemble authentic images. This adversarial training paradigm fosters the refinement of our model over time, enabling it to capture intricate color details inherent in real-world images.

In summary, the `GANLoss` class plays a critical role in facilitating adversarial learning and guiding the training of our colorization model. By leveraging advanced loss functions and label generation techniques, we can train our model to achieve impressive results, effectively bridging the gap between grayscale and vibrant color images.

G. Building Final Model and Training

The `MainModel` class, as shown in Figure G below, is the linchpin of our colorization framework, orchestrating the intricate dance between the generator and discriminator networks to achieve high-quality colorization results. Its architecture encapsulates the core components necessary for training and managing the complex interplay between these networks.

At its core, the `MainModel` class encapsulates the essence of our colorization workflow. During initialization, it lays the foundation by instantiating the generator (`net_G`) and discriminator (`net_D`) networks, each tailored to fulfill specific roles within the colorization pipeline. This modular approach not only affords flexibility in network architecture design but also facilitates experimentation with different configurations to optimize performance. As the training unfolds, the `MainModel` class takes on the role of conductor, directing the flow of data through the colorization pipeline. Its `optimize` method serves as the nexus where the generator and discriminator converge, iteratively refining their parameters to minimize the gap between predicted and ground truth colorizations.

```python
class MainModel(nn.Module):
    def __init__(self, net_G=None, lr_G=2e-4, lr_D=2e-4,
                 beta1=0.5, beta2=0.999, lambda_L1=100.):
        super().__init__()

        self.device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        self.lambda_L1 = lambda_L1

        if net_G is None:
            self.net_G = init_model(Unet(input_c=1, output_c=2, n_down=8, num_filters=64), self.device)
        else:
            self.net_G = net_G.to(self.device)
        self.net_D = init_model(PatchDiscriminator(input_c=3, n_down=3, num_filters=64), self.device)
        self.GANcriterion = GANLoss(gan_mode='vanilla').to(self.device)
        self.L1criterion = nn.L1Loss()
        self.opt_G = optim.Adam(self.net_G.parameters(), lr=lr_G, betas=(beta1, beta2))
        self.opt_D = optim.Adam(self.net_D.parameters(), lr=lr_D, betas=(beta1, beta2))

    def set_requires_grad(self, model, requires_grad=True):
        for p in model.parameters():
            p.requires_grad = requires_grad

    def setup_input(self, data):
        self.L = data['L'].to(self.device)
        self.ab = data['ab'].to(self.device)

    def forward(self):
        self.fake_color = self.net_G(self.L)

    def backward_D(self):
        fake_image = torch.cat([self.L, self.fake_color], dim=1)
        fake_preds = self.net_D(fake_image.detach())
        self.loss_D_fake = self.GANcriterion(fake_preds, False)
        real_image = torch.cat([self.L, self.ab], dim=1)
        real_preds = self.net_D(real_image)
        self.loss_D_real = self.GANcriterion(real_preds, True)
        self.loss_D = (self.loss_D_fake + self.loss_D_real) * 0.5
        self.loss_D.backward()

    def backward_G(self):
        fake_image = torch.cat([self.L, self.fake_color], dim=1)
        fake_preds = self.net_D(fake_image)
        self.loss_G_GAN = self.GANcriterion(fake_preds, True)
        self.loss_G_L1 = self.L1criterion(self.fake_color, self.ab) * self.lambda_L1
        self.loss_G = self.loss_G_GAN + self.loss_G_L1
        self.loss_G.backward()

    def optimize(self):
        self.forward()
        self.net_D.train()
        self.set_requires_grad(self.net_D, True)
        self.opt_D.zero_grad()
        self.backward_D()
        self.opt_D.step()

        self.net_G.train()
        self.set_requires_grad(self.net_D, False)
        self.opt_G.zero_grad()
        self.backward_G()
        self.opt_G.step()
```

Figure G. Final Model Code Snippet

Within the training loop, the generator endeavors to produce colorized images (`fake_color`) that are indistinguishable from ground truth colorizations. To this end, it navigates a dual objective, seeking to both deceive the discriminator and align its output with the target colorizations. This delicate balancing act is facilitated by the adversarial loss (`loss_G_GAN`), which measures the generator's success in outwitting the discriminator, and the L1 loss (`loss_G_L1`), which quantifies the pixel-level disparity between generated and target colorizations.

The use of load and save checkpoints is to help facilitate training of the model over long periods of time as this model takes about 10-12 hours of training which is around 100-120 epochs in order for results to show. Therefore, by using checkpoints it helps save progress when unexpected problems arise.

Meanwhile, the discriminator diligently scrutinizes both real and generated images, honing its ability to discriminate between authentic and synthetic colorizations. By providing feedback to both the generator and discriminator, the `MainModel` class fosters a symbiotic relationship between these networks, driving them towards mutual improvement and convergence.

Beyond its role in training supervision, the `MainModel` class also assumes responsibility for checkpoint management, ensuring the preservation of model states across training sessions. This critical functionality not only safeguards against data loss but also enables seamless resumption of training and facilitates reproducibility of results. In essence, the `MainModel` class serves as the backbone of our colorization framework, providing a

robust infrastructure for training, coordinating, and fine-tuning the intricate neural networks that power our colorization pipeline. Its design reflects a commitment to usability, versatility, and performance, empowering researchers and practitioners to unlock the full potential of deep learning-based colorization techniques.

H. Evaluating the Model

After the training phase, where the `MainModel` undergoes iterative optimization to improve its performance, the evaluation stage becomes paramount for assessing its effectiveness in colorizing images accurately. In this phase, we leverage a comprehensive set of metrics to gauge the model's performance, providing nuanced insights into the discriminative and generative capabilities of the neural network architecture.

Central to the evaluation process are metrics such as `loss_D_real` and `loss_D_fake`, which serve as fundamental indicators of the discriminator's proficiency in discerning between real and synthetic colorizations. These metrics quantify the adversarial losses incurred by the discriminator when evaluating pairs of real and fake colorized images. A lower `loss_D_real` signifies that the discriminator can effectively identify authentic colorizations from the dataset, while a higher `loss_D_fake` suggests that it struggles to distinguish between genuine and synthetic images, possibly indicating areas for improvement in the generative process.

In parallel, the `loss_G_GAN` metric plays a pivotal role in assessing the generator's ability to produce synthetic colorizations that deceive the discriminator effectively. This adversarial loss measures the degree to which the generator can generate colorized images that closely resemble real ones, thereby fooling the discriminator into classifying them as authentic. A lower `loss_G_GAN` indicates that the generator excels in generating convincing colorizations, demonstrating its proficiency in capturing the underlying distribution of real images and synthesizing visually plausible outputs.

Complementing the adversarial loss, the `loss_G_L1` metric offers insights into the fidelity of the generated colorizations compared to the ground truth. This metric quantifies the pixel-wise differences between the generated colorized images and the corresponding ground truth images, providing a measure of the model's ability to accurately reproduce colors present in the input grayscale images. A lower `loss_G_L1` signifies that the generator can faithfully replicate the color distribution of the dataset, resulting in high-quality colorized outputs that closely align with the original images.

By collectively analyzing these metrics, we gain a comprehensive understanding of the `MainModel`'s performance, allowing us to identify strengths, weaknesses, and areas for improvement in the colorization pipeline. Furthermore, these metrics serve as valuable feedback during the model development process, guiding the selection of hyperparameters, loss functions, and network architectures to optimize colorization performance iteratively. In conclusion, the evaluation of the `MainModel` using these metrics forms a critical aspect of our colorization methodology, facilitating continuous refinement and enhancement of our deep learning-based approach to image colorization.

VI. **RESULTS AND DISCUSSION**

A. Data Preparation Results

Upon examining the output from the data preparation phase, it becomes evident that the dataset has been effectively processed into batches suitable for training and evaluation. The dimensions of the grayscale images (L) in each batch, denoted as [16, 1, 256, 256], indicate that 16 images are included per batch, with each image possessing a single channel and being resized to 256x256 pixels. Similarly, the dimensions of the color information (ab) in the Lab color space, represented as [16, 2, 256, 256], reveal that each batch contains 16 images, each having two color channels ('a' and 'b') and being resized to 256x256 pixels.

```
torch.Size([16, 1, 256, 256]) torch.Size([16, 2, 256, 256])
500 125
```

Figure H. Data Preparation Output

This output signifies the successful preprocessing of the dataset, ensuring compatibility with the model architecture. The grayscale images (L) serve as input to the model, providing the luminance information, while the color information (ab) complements it by supplying the chrominance details. By organizing the data into batches, the training and evaluation processes can proceed efficiently, enabling the model to learn and generate accurate colorizations based on the provided grayscale images. Understanding these dimensions is pivotal for configuring the model architecture and optimizing training procedures to achieve desired performance metrics.

B. Building Generator(U-Net Block) Results

The output provided showcases the architecture of a U-Net model, revealing its structural composition and configuration. The U-Net consists of a series of convolutional and transpose convolutional layers organized in a hierarchical manner, forming a U-shaped architecture.

```
Unet(
  (model): UnetBlock(
    (model): Sequential(
      (0): Conv2d(1, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
      (1): UnetBlock(
        (model): Sequential(
          (0): LeakyReLU(negative_slope=0.2, inplace=True)
          (1): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
          (2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
          (3): UnetBlock(
            (model): Sequential(
              (0): LeakyReLU(negative_slope=0.2, inplace=True)
              (1): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
              (2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
              (3): UnetBlock(
                (model): Sequential(
                  (0): LeakyReLU(negative_slope=0.2, inplace=True)
                  (1): Conv2d(256, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
                  (2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                  (3): UnetBlock(
                    (model): Sequential(
                      (0): LeakyReLU(negative_slope=0.2, inplace=True)
                      (1): Conv2d(512, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
                      (2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                      (3): UnetBlock(
                        (model): Sequential(
                          (0): LeakyReLU(negative_slope=0.2, inplace=True)
                          (1): Conv2d(512, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
                          (2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                          (3): UnetBlock(
                            (model): Sequential(
                              (0): LeakyReLU(negative_slope=0.2, inplace=True)
                              (1): Conv2d(512, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
                              (2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                              (3): UnetBlock(
                                (model): Sequential(
                                  (0): LeakyReLU(negative_slope=0.2, inplace=True)
                                  (1): Conv2d(512, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
                                  (2): ReLU(inplace=True)
                                  (3): ConvTranspose2d(512, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
                                  (4): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                                )
                              )
                              (4): ReLU(inplace=True)
                              (5): ConvTranspose2d(1024, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
                              (6): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                              (7): Dropout(p=0.5, inplace=False)
                            )
                          )
                          (4): ReLU(inplace=True)
                          (5): ConvTranspose2d(1024, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
                          (6): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                          (7): Dropout(p=0.5, inplace=False)
                        )
                      )
                      (4): ReLU(inplace=True)
                      (5): ConvTranspose2d(1024, 512, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
                      (6): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                      (7): Dropout(p=0.5, inplace=False)
                    )
                  )
                  (4): ReLU(inplace=True)
                  (5): ConvTranspose2d(1024, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
                  (6): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
                )
              )
              (4): ReLU(inplace=True)
              (5): ConvTranspose2d(512, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
              (6): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
            )
          )
          (4): ReLU(inplace=True)
          (5): ConvTranspose2d(256, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
          (6): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
        )
      )
      (2): ReLU(inplace=True)
      (3): ConvTranspose2d(128, 2, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))
      (4): Tanh()
    )
  )
)
```

Figure I. Generator (U-Net) Architecture

At the core of the U-Net model lies the UnetBlock module, which encapsulates a sequence of convolutional layers followed by activation functions and batch normalization. Each UnetBlock module is nested within another, allowing for a multi-scale feature extraction process. Starting from the initial convolutional layer, the model progressively downsamples the input through convolutional operations with a stride of 2, effectively reducing the spatial dimensions of the feature maps. Subsequently, the model utilizes transpose convolutional layers to upsample the feature maps, gradually restoring the original spatial dimensions. The UnetBlock module employs leaky ReLU activation functions, which introduce non-linearity into the model and help alleviate the vanishing gradient problem during training. Additionally, batch normalization layers are incorporated to stabilize the training process and accelerate convergence. The final layers of the U-Net architecture consist of a convolutional transpose operation followed by a Tanh activation function. This arrangement generates the colorized output image, with the Tanh function ensuring that the pixel values are bounded within the range [-1, 1].

Overall, the U-Net architecture demonstrates a well-defined structure that enables effective feature extraction and spatial transformation, making it suitable for various image processing tasks, including colorization.

C. Building Discriminator Results

The provided output unveils the architecture of a Patch Discriminator model, elucidating its structural components and configuration. The Patch Discriminator comprises a series of convolutional layers organized within a sequential module.

```
PatchDiscriminator(
  (model): Sequential(
    (0): Sequential(
      (0): Conv2d(3, 64, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1))
      (1): LeakyReLU(negative_slope=0.2, inplace=True)
    )
    (1): Sequential(
      (0): Conv2d(64, 128, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): LeakyReLU(negative_slope=0.2, inplace=True)
    )
    (2): Sequential(
      (0): Conv2d(128, 256, kernel_size=(4, 4), stride=(2, 2), padding=(1, 1), bias=False)
      (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): LeakyReLU(negative_slope=0.2, inplace=True)
    )
    (3): Sequential(
      (0): Conv2d(256, 512, kernel_size=(4, 4), stride=(1, 1), padding=(1, 1), bias=False)
      (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (2): LeakyReLU(negative_slope=0.2, inplace=True)
    )
    (4): Sequential(
      (0): Conv2d(512, 1, kernel_size=(4, 4), stride=(1, 1), padding=(1, 1))
    )
  )
)
```

Figure J. Discriminator Architecture

Beginning with the initial convolutional layer, the model accepts input images with three channels, representing the RGB color space. This convolutional layer employs a 4x4 kernel size with a stride of 2, facilitating down-sampling of the input images while preserving important spatial information. The subsequent activation function, Leaky ReLU, introduces non-linearity into the model, aiding in feature extraction.

Continuing, the Patch Discriminator incorporates additional convolutional layers, each followed by batch normalization and Leaky ReLU activation functions. These layers progressively extract higher-level features from the downsampled input images, contributing to the discrimination process. Batch normalization layers normalize the activations of the previous layer, stabilizing the training process and accelerating convergence.

The final convolutional layer of the Patch Discriminator model outputs a single-channel feature map, representing the discriminator's decision for each patch of the input image. This decision is determined based on whether the patch is classified as real or fake, assisting in the adversarial training process of the Generative Adversarial Network (GAN).

Overall, the Patch Discriminator architecture is designed to scrutinize local patches of input images, enabling finer discrimination between real and fake patches. This approach enhances the model's ability to capture subtle details and nuances, making it well-suited for tasks such as image colorization, where localized changes are crucial for maintaining image fidelity.

D. Training and Evaluation Results

The training output provides a detailed snapshot of the model's performance and progression throughout the training process.

```
Epoch 1/100
Iteration 250/500
loss_D_fake: 0.49720
loss_D_real: 0.50376
loss_D: 0.50048
loss_G_GAN: 1.44020
loss_G_L1: 9.46268
loss_G: 10.90288
```

Figure K. Epoch 1 Metrics

```
Epoch 29/100
Iteration 250/500
loss_D_fake: 0.50930
loss_D_real: 0.51804
loss_D: 0.51367
loss_G_GAN: 1.37065
loss_G_L1: 8.04603
loss_G: 9.41669
```

Figure L. Epoch 29 Metrics

Within the context of the first epoch (`Epoch 1/100`), the iteration count `Iteration 250/500` signifies that the model has traversed half of the anticipated 500 batches scheduled for training. This delineation helps in understanding the pacing and advancement of the training procedure, offering valuable insights into how the model's performance evolves over time.

A crucial aspect of the training output is the assortment of performance metrics pertaining to both the discriminator and the generator losses. These metrics, such as `loss_D_fake`, `loss_D_real`, and `loss_D`, offer a nuanced understanding of the discriminator's behavior when confronted with fake and real images, as well as its overall performance in discerning between the two. Similarly, metrics like `loss_G_GAN`, `loss_G_L1`, and `loss_G` shed light on the generator's adversarial and L1 losses, providing a comprehensive view of its efficacy in generating realistic images.

Amidst the log entries documenting loss metrics, warning messages regarding potential issues with color data further punctuate the training output. These warnings, which highlight instances where color data falls outside the expected range, serve as alerts for potential anomalies or discrepancies that may impact the training process or the quality of generated images.

The completion of the first epoch is demarcated by the processing of the final batch (`Iteration 500/500`). This signifies the culmination of an initial training cycle, where the model has been exposed to and learned from a substantial portion of the training dataset.

In summation, the training output encapsulates a wealth of information regarding the model's performance, losses, and potential challenges encountered during training. This comprehensive record serves as a valuable resource for analyzing and optimizing the training process, ultimately contributing to the refinement and enhancement of the model's capabilities.

The above figures only display epochs uptil 29 but since we use checkpoints to save and load progress, the epochs don't tell the true story of the training time as the epochs reset everytime we load a checkpoint. Hence, the model has been trained for a lot longer than just 29 epochs. It just so happens to show 29 epochs right now as its 29 epochs further down the line than its previous checkpoint which already has the model trained for about 64 epochs.

E. Final Results

Figure M. Final Results after 100 Epochs

The evaluation of the baseline model reveals both its strengths and limitations in colorization tasks. While the model demonstrates a rudimentary understanding of common objects typically found in images, such as skies and trees, its output falls short of delivering visually appealing results. Upon closer inspection, several deficiencies become apparent, casting doubt on the model's effectiveness.

One notable drawback is the model's inability to accurately determine the color of rare or less common objects present in the images. While it may perform adequately with familiar objects, its performance falters when tasked with coloring less prevalent elements. This limitation hampers the model's versatility and renders it less suitable for scenarios involving a diverse array of subjects or themes.

Furthermore, the output generated by the baseline model exhibits instances of color spillovers and anomalies, detracting from the overall quality of the colorized images. For example, in the center of the first image of the second row, a circular mass of color is observed, which appears unnatural and detracts from the authenticity of the image. Such artifacts undermine the fidelity and realism of the colorized output, diminishing its utility in practical applications.

Upon reflection, it becomes evident that the baseline model's performance is inherently constrained by the size and composition of the dataset used for training. With a limited dataset, the model lacks exposure to a diverse range of examples, hindering its ability to generalize effectively to unseen data. Consequently, the model struggles to produce satisfactory results across a broad spectrum of images, particularly those featuring rare or unconventional objects.

In conclusion, while the baseline model demonstrates a basic understanding of common objects in images, its output falls short of meeting the desired standards of quality and fidelity. The presence of color artifacts, limitations in handling rare objects, and overall subpar performance underscore the need for more sophisticated approaches and larger, more diverse datasets to achieve superior results in colorization tasks.

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