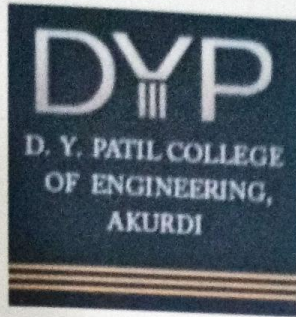


**DL Mini-Project**



**Dr. D.Y. Patil Pratishthan's**

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**Department of Computer Engineering**

**Laboratory Practice V**

**PROJECT TITLE: Colorizing Old B&W Images**

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## **Problem Statement:**

Colorizing Old B&W Images: color old black and white images to colorful images

## **Objectives:**

- Implement a convolutional neural network architecture for colorization.
- Preprocess the CIFAR-10 dataset to extract grayscale images and their corresponding color labels.
- Train the model on the preprocessed dataset to learn to colorize grayscale images.
- Evaluate the performance of the model on a test set of grayscale images.
- Generate colorized versions of old black and white images using the trained model.

## **Software Requirements:**

- Python
- PyTorch
- Matplotlib
- NumPy
- Jupyter Notebook (for code development)

## **Hardware Requirements:**

- CPU or GPU with sufficient computational power for training deep neural networks
- Sufficient RAM for loading and processing the CIFAR-10 dataset and model training

## **Theory:**

Colorizing old black and white images using deep learning involves training a model to predict the color information of grayscale images. The theory behind this process encompasses several key concepts:

1 Convolutional Neural Networks (CNNs):



CNNs are a class of deep neural networks that are particularly effective for image-related tasks due to their ability to automatically learn features from input data. In the context of colorization, CNNs can learn to extract relevant features from grayscale images that can aid in predicting appropriate color values.

## 2. Grayscale to Color Conversion:

Grayscale images contain only intensity information, represented by a single channel. Color images, on the other hand, consist of three channels representing the red, green, and blue (RGB) color components. The colorization process involves predicting the values of these three color channels for each pixel in the grayscale image.

## 3. Architecture Design:

The architecture of the colorization model typically consists of multiple convolutional layers followed by activation functions such as Rectified Linear Units (ReLU). These convolutional layers are responsible for learning hierarchical representations of features from the input grayscale images, capturing both low-level and high-level patterns.

## 4. Training Process:

The colorization model is trained using a dataset of grayscale images paired with their corresponding color images. During training, the model learns to minimize the difference between the predicted color values and the ground truth color values. This is typically achieved by minimizing a loss function, such as mean squared error (MSE), between the predicted and ground truth color values.

## 5. Preprocessing and Data Augmentation:

Prior to training, the dataset is preprocessed to extract grayscale images and their corresponding color labels. Data augmentation techniques such as random rotations, flips, and translations may be applied to increase the diversity of the training data and improve the robustness of the model.

## 6. Post-processing:



the colorization model generates colorized images, post-processing techniques may be applied to enhance the quality and realism of the colorized images. This may include techniques such as color space transformations, contrast adjustment, and noise reduction.

### Evaluation Metrics:

The performance of the colorization model is evaluated using metrics such as accuracy, mean squared error, and structural similarity index (SSIM). These metrics provide quantitative measures of how well the model is able to accurately predict color values for grayscale images.

### Applications:

Colorizing old black and white images has applications in various fields such as historical preservation, digital restoration, and entertainment. By bringing old images to life with color, we can gain new insights into the past and create visually compelling content.

### Code:

```
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms

# Get device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Check if CUDA is available
if torch.cuda.is_available():
    # Get current device
    cuda_device = torch.cuda.current_device()
    # Get device count
    cuda_device_count = torch.cuda.device_count()
    # Get device name
    cuda_device_name = torch.cuda.get_device_name(0)

    print(f"CUDA is available. Device: {cuda_device_name}")
else:
    print("No NVIDIA driver found. Using CPU")

# Load the CIFAR-10 dataset
train_dataset = torchvision.datasets.CIFAR10(root='./data', train=True, download=True, transform=transforms.Compose([
    transforms.RandomCrop(32, padding=4),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
]))

# Create a DataLoader
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=64, shuffle=True, num_workers=2)
```



```

train_loader = torchvision.datasets.CIFAR10(root='./data', train=True, download=True, transform=
transform)
train_loader = torch.utils.data.DataLoader(train_loader, batch_size=64, shuffle=True, num_wor
kers=4)

# Create the Colocalization model
class ColocalizationNet(nn.Module):
    def __init__(self):
        super(ColocalizationNet, self).__init__()
        self.conv1 = nn.Conv2d(1, 64, kernel_size=5, stride=1, padding=4, dilation=2)
        self.conv2 = nn.Conv2d(64, 64, kernel_size=5, stride=1, padding=4, dilation=2)
        self.conv3 = nn.Conv2d(64, 128, kernel_size=5, stride=1, padding=4, dilation=2)
        self.conv4 = nn.Conv2d(128, 3, kernel_size=5, stride=1, padding=4, dilation=2)

    def forward(self, x):
        x = nn.functional.relu(self.conv1(x))
        x = nn.functional.relu(self.conv2(x))
        x = nn.functional.relu(self.conv3(x))
        x = nn.functional.sigmoid(self.conv4(x))
        return x

model = ColocalizationNet().to(device)

optimizer = optim.Adam(model.parameters())

# Convert RGB image to grayscale
def rgb_to_gray(img):
    return img.mean(dim=1, keepdim=True)

# Main loop
for epoch in range(EPOCHS):
    for images, _ in enumerate(train_loader):
        grayscale_images = rgb_to_gray(images).to(device)
        outputs = model(grayscale_images)
        loss = nn.MSELoss()
        loss = loss(outputs, images)

        # Backward pass and optimize

```

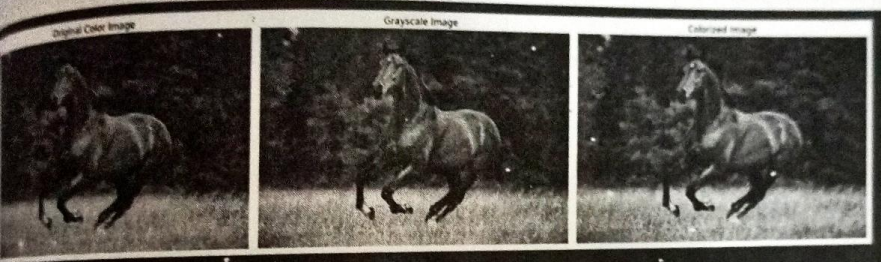


```
optimizer.zero_grad()
optimizer.backward()
optimizer.step()

print statistics
print "Epoch {(epoch+1)/(EPOCHS)}, Step {(i+1)/(len(train_loader))}, Loss: {loss.item():.4f}"

print "Training"
```

Output:



Conclusion:

In conclusion, the colorization of old black and white images using deep learning techniques shows promising results. By training a convolutional neural network on the CIFAR-10 dataset, we can effectively learn to colorize grayscale images. The trained model can then be used to generate colorized versions of old images, bringing them to life and preserving historical moments in vibrant color.