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Black and White Image Colorization Using Convolutional Neural Networks

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***Abstract*—Colorization of black and white images has become increasingly important with the advent of high-quality and high-resolution pictures in modern-day life. This project proposes a method for converting black and white pictures to color pictures. This project is mainly designed for coloring black and white images using the Deep learning Algorithms like CNN (Convolutional Neural Networks. This proposed method produced great results with a very little mean square error of 0.3174.**

Keywords—Colorization, Grayscale, Deep Learning, CNN.

I. INTRODUCTION

The act of adding color to a grayscale image involves taking a grayscale image as an input, and producing an RGB formatted output, resulting in a color image which is commonly referred to as Image Colorization. Black and white image colorization is an interesting and challenging problem in computer vision .This project goal is to automatically colorize grayscale images, which can be useful in various applications such as restoration of old photos, movie colorization, and even assist people with color vision deficiencies to better understand the content of an image. The primary objective of image colorization remains to transform a monochrome image into a colored version that is not only aesthetically pleasing but also comprehensible to human perception.

There are many wide applications for Image Colorization in the fields of Photography of astronomical objects. Coloring an image can make it easier to understand. The application of colorization to images has yielded positive outcomes across multiple domains. In the medical and healthcare sectors, for instance, colorization has proven to be particularly beneficial. Given that most devices and apparatus utilized in medical procedures produce grayscale images, colorizing such images has aided researchers and medical professionals in enhancing their comprehension and interpretation.

Improving the visualization of medical images through colorization techniques is essential for achieving the UNSDG3, which aims to promote good health and well-being for all. The UNSDG3 health logo (United Nations, n.d.) serves as a symbol of this important goal.

Black and white image colorization has many applications. As we know that storage and transmission of color images takes a lot of space and time, the best option can be storing them and transmitting the black and white images and later converting them into color images using this method. This saves a lot of space and time.

The other application is infrared image colorization. The use of colorization in infrared images is important because it can help to enhance the interpretation and analysis of the images. Infrared images are typically captured in grayscale, with variations in temperature being represented as different shades of gray. Colorized images can be particularly useful for presentations, reports, and other communication purposes.

Now mostly, everyone has many gadgets that can take clear pictures of them. But in the olden days, all these updated gadgets were not available, and they used to take images in black and white. Colorizing images facilitates the recreation of memories. In India, for instance, popular films like Maya Bazar and Mughal-e-Azam were transformed into colorized versions, attracting significant crowds to theaters and garnering blockbuster success.

To colorize an image, various subtasks must be addressed, including color localization, object classification, and segmentation comprehension. With advancements in Deep Learning, technology has significantly progressed from manual to automated solutions.

Currently, numerous manual techniques exist for colorization, such as hand-drawn images, general color assumptions, or the provision of comparable images that are more semantically aligned with the grayscale image. These all procedures are not fully successful and there is a need to find a solution. The problem of Image Colorization is still perplexing. When learning based image colorization is considered, a gray scale image can be colorized based on what it has been learnt. For example, a dog can be brown, or white depending upon the breed. The network should be trained properly for accurate results. Due to its proficiency in processing visual data, the convolutional neural network has been selected from a variety of neural network models. Many solutions are present, with CNN being one of the primary candidates. Fig.1 shows a sample example of black and white images and their corresponding color images.

For this project, a model utilizing convolutional neural networks was designed and implemented and their qualitative and quantitative comparisons are also provided. Regularization techniques are also applied to the model to increase the performance of the model. Performance metrics like loss and MSE and PSNR are also calculated to analyze the accuracies of the results.

Fig. 1. Example input grayscale photo and output photo after colorization.

II. LITERATURE REVIEW

Convolutional Neural Networks are widely used in many tasks including black and white image colorization. In this model, it takes a black and white image as input and predicts the corresponding-colored image.

The paper [1] presents a new technique for gray scale image colorization based on Convolutional Neural Networks (CNNs) and a pre-trained classification network. The authors demonstrate the effectiveness of their method through experiments on various datasets.

The paper [2] presents a deep learning-based technique for colorizing gray scale images. The authors employ a combination of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to achieve realistic colorization results.

The paper [3] proposes a technique for colorizing gray scale images of human faces using deep learning-based methods. The authors employ a combination of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) to generate realistic colorizations. They evaluate their approach on a dataset of human faces and compare it with state-of-the-art methods, demonstrating its effectiveness and outperforming existing techniques.

The paper [4] proposes a fast approach for colorizing gray scale images using Convolutional Neural Networks (CNNs). The authors present a modified U-Net architecture that reduces the computational complexity and improves the speed of the colorization process.

A technique for manual colorization was developed by Anat Levin et al. [5], which adds color to grayscale images. This method assigns colors to image components with constant value and intensity, resulting in a colorized image. Unlike other manual techniques, the user does not need to manually color each component or worry about object boundaries. The main advantage of this method is its efficiency, as it saves time and avoids adding unnecessary colors.

The paper [6] proposes a prototype for integrating colorization and super resolution models using machine learning techniques. The authors employ a combination of Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) to enhance the resolution of gray scale images while simultaneously colorizing them.

The paper [7] proposes an approach for image colorization using deep transfer learning. The authors employ a pre-trained Convolutional Neural Network (CNN) as a feature extractor to extract image features from a source dataset, which are then used to train a separate colorization network.

The paper [8] presents an image colorization algorithm based on an improved Generative Adversarial Network (GAN). The authors propose a novel loss function to improve the performance of the GAN-based colorization model, which helps to generate more visually pleasing and realistic colorized images.

The paper [9] proposes a self-similarity-based colorization approach, which utilizes the local structure of the image to achieve better colorization results. The method uses a clustering algorithm to group similar patches, and then applies color transfer to map colors from a reference image to the grayscale image patches.

Zezhou Cheng [10] tackled the challenging problem of converting grayscale images to color. Traditionally, human assistance has been required to achieve high-quality results, particularly in coloring landscapes or other complex scenes. To overcome this limitation, Cheng proposed an automated colorization approach using convolutional neural networks (CNNs) that can generate accurate and visually pleasing colorizations without human intervention. The goal of the paper is to explore how CNN-based methods can improve the quality of colorization and make the process more efficient.

The paper [11] proposes a method for colorizing near-infrared (NIR) images using a convolutional neural network (CNN) with a perceptual loss. The proposed method aims to improve the visual quality of colorized NIR images by considering the human perception of color. The results show that the proposed method achieves better performance compared to traditional methods for colorizing NIR images.

This paper [12] presents an interactive deep colorization technique that allows users to selectively colorize specific regions of grayscale images. The proposed approach combines a deep neural network with a user-guided interface to achieve accurate and flexible colorization results.

The paper [13] presents an automatic colorization method for both images and videos using deep learning. The proposed method uses a convolutional neural network (CNN) to generate color channels for grayscale images and videos.

In this paper [14], the authors propose an automatic colorization method for black and white images from Chinese films using convolutional neural networks (CNNs). The proposed method takes into consideration the characteristics of Chinese films and incorporates a gradient weighting loss function to improve the colorization accuracy. The experimental results demonstrate that the proposed method outperforms the existing colorization methods on a Chinese film dataset.

The Colorful Image Colorization paper [15] proposes an automatic colorization method based on a deep neural network trained on a large dataset of color images. The network maps the input grayscale image to an output color image by using a combination of global and local features.

This paper [16] provides a comprehensive survey of various image colorization techniques and datasets. The authors review classical and deep learning-based colorization methods and discuss their strengths and limitations. Additionally, they introduced a new large-scale image colorization dataset, COCO-Color, which contains over 200,000 images.

The paper [17] proposes a deep learning-based approach for colorizing black and white images. The authors use a convolutional neural network (CNN) for feature extraction and a generative adversarial network (GAN) for generating the colored output.

This paper [18] presents a method for colorizing black and white images using deep learning. The authors use a convolutional neural network (CNN) for the colorization task and train it on a large dataset of colored images. They also evaluate the performance of their method on several benchmarks and show that it outperforms existing colorization methods.

The paper [19] proposes a remote sensing image colorization method based on a multiscale SEnet GAN model. The model incorporates spatial and channel-wise attention mechanisms to improve colorization accuracy and reduce artifacts. The proposed method is evaluated on a publicly available remote sensing dataset and achieves promising results compared to state-of-the-art methods.

This paper [20] presents a deep learning-based approach for near-infrared image colorization using image-to-image translation. The proposed method utilizes a conditional generative adversarial network (cGAN) with a perceptual loss function to improve colorization accuracy. The results show that the proposed method outperforms traditional methods and previous deep learning approaches in terms of colorization quality and accuracy.

Jeff Hwang and You Zhou [21] developed a system for automatically colorizing black and white images using convolutional neural networks, without the need for human input. They experimented with various architectures, objectives, color spaces, and formulations to address the problem. By analyzing different classification methods, they were able to determine the appropriate colors for each object in the image.

III. Dataset Description

An image dataset called MIRFLICKR25k is used to train the model for image colorization.

The images consist of different random images of humans, objects, places, things, animals. The images are of different dimensions hence, preprocessing those images is done before feeding to the model.

Our input to the model is a grayscale image. Gray scale images have only one channel and their pixel values range from 0 to 127. RGB images have three channels, and the pixel intensity values are between 0 and 255. Both grayscale and RGB images are from this dataset only. Output is the predicted colored image of the grayscale image.

IV. Methodology

A convolutional neural network (CNN) architecture for black and white image colorization is built with regularization techniques such as dropout and L2 regularizer to prevent overfitting. The network is then trained using Adam optimizer with a suitable learning rate. During training, the network weights are updated iteratively to minimize the mean squared error (MSE) or cross-entropy loss between the predicted and ground truth color images. The trained network is then tested on a separate testing dataset to evaluate its performance using various metrics such as MSE, Loss, PSNR.

The image was preprocessed for input into a neural network. Preprocessing of colored training images involved color space conversion, resizing, and normalization. Subsequently, the model was trained and evaluated.

A. *CNN Architecture:*

Convolutional Neural Network (CNN) is a type of deep learning architecture that is commonly used for image and video analysis. CNNs are designed to learn spatial hierarchies of features automatically and adaptively from input data. They use convolutional layers that apply filters to the input image, pooling layers that down sample the feature maps to reduce the spatial dimensions, and fully connected layers that perform the final classification.

```
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, None, None, 1)]   0

 conv2d (Conv2D)             (None, None, None, 8)     80

 dropout (Dropout)           (None, None, None, 8)     0

 conv2d_1 (Conv2D)           (None, None, None, 16)    1168

 conv2d_2 (Conv2D)           (None, None, None, 16)    2320

 dropout_1 (Dropout)         (None, None, None, 16)    0

 conv2d_3 (Conv2D)           (None, None, None, 32)    4640

 conv2d_4 (Conv2D)           (None, None, None, 32)    9248

 dropout_2 (Dropout)         (None, None, None, 32)    0

 up_sampling2d (UpSampling2D  (None, None, None, 32)   0
 )

 conv2d_5 (Conv2D)           (None, None, None, 32)    9248

 up_sampling2d_1 (UpSampling  (None, None, None, 32)   0
 2D)

 conv2d_6 (Conv2D)           (None, None, None, 16)    4624

 up_sampling2d_2 (UpSampling  (None, None, None, 16)   0
 2D)

 conv2d_7 (Conv2D)           (None, None, None, 2)     290

 tf.reshape (TFOpLambda)     (104, 104, 2)             0

 tf.image.resize (TFOpLambda  (100, 100, 2)            0
 )

 tf.reshape_1 (TFOpLambda)   (1, 100, 100, 2)          0

=================================================================
Total params: 31,618
Trainable params: 31,618
Non-trainable params: 0
```

Fig. 2. Figure describing CNN architecture.

Fig2 shows the architecture of our CNN model. The input to the model is given a grayscale image. The first layer of the network is a Conv2D layer with 8 filters, a filter size of 3x3, a stride of 2, and ReLU activation. This layer samples the image by a factor of 2. A dropout layer is then applied with a rate of 0.2 to prevent overfitting. The next layer has 16 filters with 3x3 size. This layer is followed by another layer with 16 filters, a filter size of 3x3, a stride of 2, and ReLU activation. Another dropout layer is applied to this layer with a rate of 0.2. The following layers consist of two more layers, each with 32 filters and a filter size of 3x3. Another dropout layer is applied after each of these layers with a rate of 0.2. The next set of layers is the up-sampling layers, which increases the resolution of the image. Finally, the output layer is another layer with 2 filters and a filter size of 3x3, with a sigmoid activation function. L2 Kernel regularizer is also used. L2 kernel regularization is a type of regularization that adds a penalty to the loss function of the model by adding the squared magnitude of the weights to the loss function. Regularization strength is set to 0.01.

B. *Plot Of Loss:*

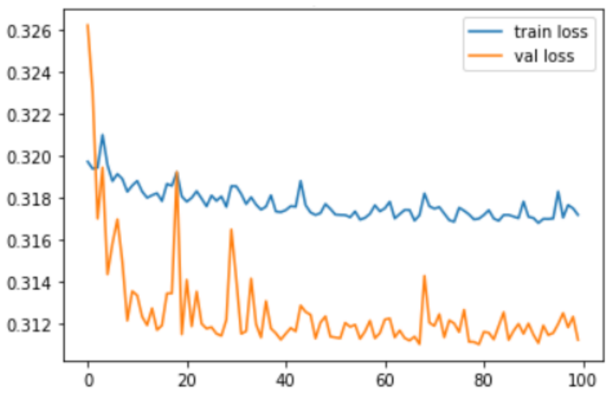

Fig. 3. Graph showing loss wrt to epochs.

Fig3 shows the loss wrt to epochs. Loss value denotes the error rate of the trained model and accuracy represents how many data points of model has been predicted correctly. From the above graph, It can be inferred that the loss decreased with an increase in the epochs.

C. *Plot Of Accuracy:*

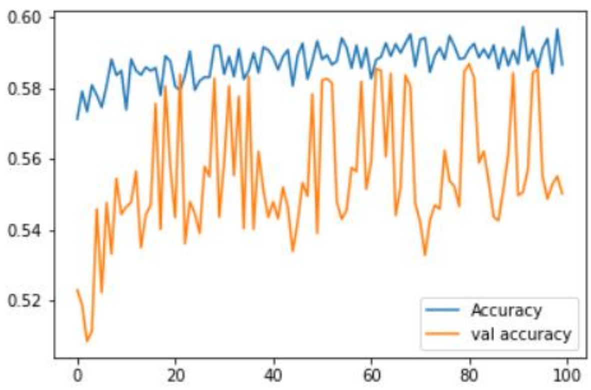

Fig. 4. Graph showing accuracy wrt to epochs.

Fig4 shows how accuracy got varied with the number of epochs. Accuracy is one of the measures to determine the performance of the model.

V. RESULTS

In black and white image colorization, various metrics are used to measure the performance of the models. PSNR (Peak Signal-to-Noise Ratio) is a commonly used metric that measures the quality of the reconstructed image by comparing it with the original image. The higher the PSNR value, the better the quality of the reconstructed image.

MSE (Mean Squared Error) is another metric that is widely used in image processing and computer vision tasks. It measures the average squared difference between the pixel values of the reconstructed image and the original image. Lower MSE values indicate better performance.

Loss is a metric that measures the difference between the predicted output of the model and the actual output. Table 5 shows the performance metrics.

Metric	Value
MSE	0.3174
Accuracy	58.02
PSNR	54.19

Fig. 5. Table showing all the performance metrics.

A. *Quantitative Analysis:*

Based on the results, the Mean Squared Error (MSE) value is 0.3174 which indicates that the average squared difference between the predicted and ground truth images is relatively low. The accuracy is 58.02%, which is moderate, and may indicate that the model has correctly colored around half of the black and white images.

The Peak Signal to Noise Ratio (PSNR) value of 54.19 indicates that the colored images are relatively close to the ground truth images in terms of signal-to-noise ratio. Higher PSNR values indicate better quality images, so a value of 54.19 is considered good.

Overall, the quantitative analysis suggests that the model has performed reasonably well in colorizing the black and white images, with relatively low MSE and a good PSNR value. However, the accuracy is moderate and may indicate that there is room for improvement.

B. *Qualitative Analysis:*

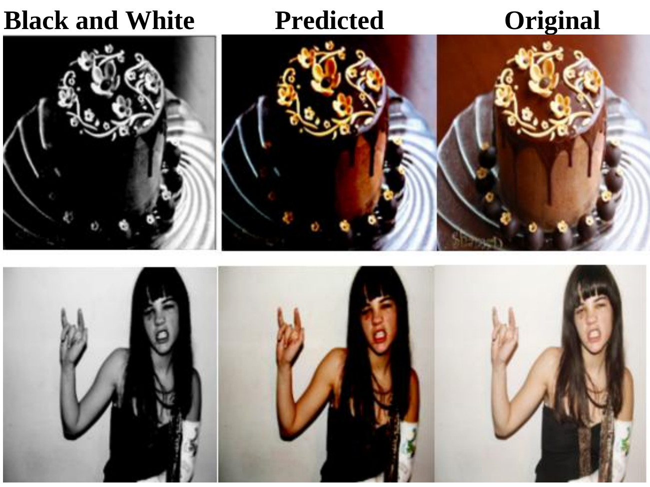

Fig. 6. Images that got colored well

Fig. 7. Images that didn't colored well.

Fig 6 and Fig 7 show the images that got colored well and not colored well.

From the above results, colorization of pictures is done to some extent, but the results can be still improved by using other networks.

In CNN model, all the neurons in each layer are connected to a small region of its previous layer and captures the spatial dependencies between the pixels of the image.

This property of CNN makes this model better than fully connected network. Our CNN model has got more accuracy and less loss during training. Training the CNN model on a larger dataset can lead to improved performance so that the model can learn better and does the colorization better. The model can also be improved by other regularization techniques like Noise Induction, Bagging, Early stop, L2 learning etc. The use of kernel regularization can help improve the generalization ability of the model and make it more robust to noise and variations in the input data.

VI. Conclusion

In this case of black and white image colorization, using regularization techniques like L2 kernel regularization and adding dropout layers will be helpful since the input data is limited and there will be a risk of overfitting to the training data of grayscale images. By using these techniques, performance can be increased.

In conclusion, black and white colorization using CNN and regularization techniques has shown great results in getting visually pleasing color images from grayscale images.

We can still work on other networks like Autoencoder, GANs (Generative Adversarial Networks), other regularization techniques for better results for black and white image colorization.

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