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|  | Black and White Image Colorization using Deep Learning |
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| A R T I C L E I N F O  Article history:  Received:  Revised:  Accepted:  *Keywords*:  Colorization,  Graphics Vision,  CNN,  RGB,  Black and White,  Image Processing.  LAB color |  | A B S T R A C T  Colorization is the process of transforming black and white images into aesthetically appealing color images. The fundamental objective is to persuade the spectator that the outcome is genuine. Automatic conversion has evolved into a difficult field that mixes machine learning and deep learning with art. . Image colorization is one method of adding style to a photograph or combining styles. Image colorization can also be used to add color to photographs that were previously black and white. This can be utilized to make an educated assumption about the picture's context and bridge the gap between the past and the present. Unlike the previous techniques, the goal of this work is to develop a high-quality fully-automatic colorization system to color the black and white images. By training our model on ImageNet images, we were able to get it to produce shots with realistic hues with 85.47% accuracy. Also the outcome of the proposed model is validated with the peer user by online survey of the colored images. |

* 1. INTRODUCTION

Image colorization is the process of assigning a color to each pixel of a target grayscale image. Colorization approaches are broadly classified as scribble-based colorization [1, 2, 3, 4, 5] and example-based colorization [6, 7, 8, 9]. Scribble-based approaches often need significant user effort to generate significant scribbles on the target grayscale photos. It is so time-consuming, especially for a novice user, to colorize a grayscale image with fine-scale features.

The example-based technique often transfers color information from a similar reference image to the target grayscale image. Finding an appropriate reference image is one of the major challenges for a user. To simplify the problem by using picture data from the Internet and provide filtering algorithms for selecting appropriate reference photos. But both the measure required additional constraints [8, 10]. An identical Internet object is required for exact per-pixel registration between the reference photos and the grayscale target image. As a result, it is confined to objects having a fixed shape like landmarks. In some cases, if the image contains text and other material with the image, then user is required to give a semantic text label as well as segmentation information for the foreground item[8,10]. In manual segmentation, it is very hard to get the original grayscale image into the colored image when image contains several complex objects. The quality of the colored image is completely depends on the selected reference image and the segmentation information provided by the user. One of the most significant uses of the grayscale image matting approach is to combine it with color transferring techniques to produce object-based colorization, which colorizers’ objects in the same picture individually. Grayscale picture colorization has uses in black and white photo editing, colorization of vintage films, and scientific drawings. Colorization may significantly improve the visual appeal of grayscale photographs and perceptually improve scientific representations.

Welsh et al. [11] suggested a grayscale picture colorization approach that performs well for natural and scientific illustrative images. Welsh et al.'s technique, in general, works best on scenarios where the image is separated into different brightness clusters or when each region has distinct textures. Their present approach, however, does not function well with human faces. These methods are too complex and require human involvement or less impact of colorization of image. As a result, it is required a pure automatic colorization method to address these limitations. One of the solutions could be the conversion of RGB color to the LAB color space.

Influenced by the current achievements of deep learning methods in image processing, we employ CNN (Convolutional Neural Network) to investigate colorization problems in photographs. However, the purpose of this research is to create a realistic colorization that may potentially trick a human observer, rather than to retrieve the actual ground truth color. As a result, our goal becomes much more attainable: model adequate grayscale semantics and textures have statistical dependencies.

In this paper, an introduction to the image colorization and its importance is presented in Introduction section. Related work section presented the previous works done by the eminent scholars. The proposed methods section presents the data set details, proposed methods and the experiment details. Result and discussion section presents results analysis and discussion and section Conclusion concludes the work.

* 1. RELATED WORK

We cover the key components of prior work in this section.

Gupta et al.(2012) [12] presented an example-based method for colorizing a grey image is presented in this research. As input, the user only needs to provide a reference color image that is semantically similar to the target image. They utilize super-pixel resolution for feature extraction from these photos, which they then use to guide colorization. The colorization procedure is sped considerably by their usage of a super-pixel representation. They create an image space voting system that uses information from adjacent super-pixels to identify and fix inaccurate color assignments, further ensuring the coherence of these first color designations in space. For example, while super-pixel representation leads to greater spatial coherence, it can be inaccurate at object edges or thin image structures while colorizing. Bleeding artifacts at object boundaries could result as an outcome of this. Second, image segments generated during color reassignment in densely textured areas are frequently very small. Because these segments have fewer super-pixels than larger segments, the image voting step's robustness is lowered. As a reason, super-pixel voting for colors within these segments becomes less accurate. Finally, this technique relies on a color exemplar that is semantically equivalent to the grey image. Consequently, when suitable color exemplars are absent, our method may fail.

Cheng et al. (2015) [13] discussed the image colorization. This study aims to develop a novel, fully automated colorization system that uses deep neural networks to eliminate human labor and reliance on color examples. Patch, DAISY, and a new semantic feature are sent into the neural network as inputs and serve as helpful but discriminative characteristics. It is, however, dependent on machine learning techniques and comes with its own set of limitations. It's designed to be trained on a large reference photo collection, such as a collection of all imaginable items. In actuality, this is impossible to achieve. It's just as tough to retrieve color information lost during the color-to-grayscale conversion.

Deshpande et al. (2015) [14] discussed large-scale image colorization. This paper predicts colorization depending on a Learch objective [24] that is actively learned. They indicate that the technique provides spatially coherent colorizations that are visually appealing and convincing when paired with histogram correction. The best performance is obtained when the information about the scene is provided. This completely automated approach achieves near-optimal results.

Iizuka et al. (2016) [15] proposed a new architecture for colorizing grayscale photos that combine international and domestic information. This method uses deep neural networks and can colorize images without human interaction. The model is trained for scene identification with a combined colorization and transmission line losses that allows it to recognize colors and adjust according to the image's aspect; for example, the sky color in a setting sun image differs from the sky color in a daylight image. Unlike other deep-learning frameworks, the suggested architecture allows us to process images of any resolution. We can also do style transfer or color a picture using the background of another, using the same approach. The method's prime requirement is that it is data-driven, meaning it can only colorize photos with identical qualities to those in the training set. To mitigate this, they test the model with a huge broad selection of interior and outdoor scene photos. Images created by humans, on the other hand, are not included. It would be essential to train a new model for the new photographs if they wanted to analyze considerably different types of images.

Pahal and Sehrawat (2016) [16] presents a deep convolution network-based method for reliably colourizing black-and-white photographic images without requiring direct human interaction. As our research has shown, this method also has the benefit and promise of employing cnn model to colourize black and white photos.We've demonstrated that structuring the problem as a classification task can result in colourized photographs that are arguably considerably more aesthetically beautiful than those generated by a basic regression-based algorithm, indicating that it has a lot of room for improvement.

Guadarrama et al.(2017)[17] PixColor generates a wide range of colorizations, and in a crowd-sourced human evaluation, the model's results outperformed other published methods on average. They get over Pixel CNN's sluggish inference difficulty by sampling only low-resolution color channels and then improving the output with a regular image-to-image CNN. In preliminary studies, the likely score (as determined by the PixelCNN model) was used to select the best sample., so there was no good correlation with human judgment.

Liu et al. (2018) [18] designed a colorization technique based on examples resistant to lighting changes between grayscale targets and color reference images. The approach manages this by executing color transfer in an illumination-independent area with few shadows and highlights. It starts by gathering several color references from the web to create an illumination-independent intrinsic reflectance picture of the sample image. The example photographs found through a web search could have been taken from various viewpoints, under various lighting conditions, and potentially different. The grayscale target image is then deconstructed into its basic reflectance and lighting components using versions of these reference images in grayscale. Color is transferred by converting the color reflectance image to the grayscale reflectance image and then relighting with the target image's illumination component to get the final output. Intrinsic colorization implies that all images are lit with white light. The intrinsic image decomposition must function for it to work. The approach needs enough reference photos from the web to supply enough registerable images with varied illuminations. Furthermore, this method is limited to colorizing static scenes using photographs of the same scene taken from similar angles. It's possible that data in the target image that differs from the reference image, or items from prior shots that have vanished, won't be colorized correctly.

Žeger, Ivana, et al (2021) [19] represents an overview and evaluation of grayscale image colorization methods and techniques applied to natural images. In this paper author has developed a colorization using deep learning methods.

Form the above discussion; it is found that most of the research required user intervention that reflects the quality of the image. Our proposed research will address this issue.

* 1. PROPOSED METHOD

This method generates a realistic color representation of a grayscale photograph. Due to the obvious limitations of this problem, previous solutions either depended heavily on human intervention or resulted in desaturated colorizations. We have developed a fully automated method for creating colorful and realistic colorizations to overcome these limitations. In this model, we have used “ImageNet Dataset” [20] to train the model, a picture database arranged as per the WordNet tree [22], with hundreds of thousands of photos depicting each node in the hierarchy. The model was trained with over a million color images and used as a feed-forward phase in a CNN during testing. For the photographs in the dataset, the RGB color scheme will be converted to “LAB color space.”

***3.1 Datasets***

ImageNet [20] is a huge database of annotated images that is utilized in computer vision and image processing. The dataset was produced with the goal of providing a resource for researchers and developers working on improving computer vision technology.

The collection contains somewhat more than 14 million pictures, somewhat more than 21 thousand sets or classes (synsets), and somewhat more than 1 million pictures with bounding box annotations, according to data on the ImageNet webpage.

Grayscale photos were filtered out of the training, validating, and testing sets because they were in the ImageNet dataset. For this experiment a total of 20,000 grayscale image, 100 legacy images and 100 man made has been used. This dataset is further splited into 70 : 20 : 10 for training, testing and validation.

***3.3 Proposed Model Description***:

The proposed method utilizes the architecture given in ref [21]. The architecture defined based on the CNN that transfer from a grayscale source to a distribution across quantized color value outputs. Here we have changed the input parameter of the given architecture to LAB color and Softmax activation function [23]. The proposed model algorithm is given in algorithm 1.

Algorithm 1

1. Input dataset and libraries
2. Preprocessing of data (extraction of data from image)
3. Convert RGB to LAB color space
4. Building the model using CNN
5. Use the L channel as the input, and then train it to anticipate the ab channels.
6. Combine the predicted (a, b) Probability distribution channels (using defined model) with the input L channel.
7. Return the Lab image to RGB image.
8. End

In this method we have used 8 convolutional layers that repeat a block of 2-3 layers. In this model we have not used any pooling layer. The up and down sampling has been used between the blocks to get correct resolution in all changes. The detailed parameter of the proposed method is given in table 1.

Table 1: Proposed model parameter description.

|  |  |  |  |
| --- | --- | --- | --- |
|  | X C | S D | Sa De |
| Data | 224 3 | - | * - |
| Conv1.1  Conv1.2 | 224 64  112 64 | 1 1  2 1 | 1 1  1 1 |
| Conv2.1Conv2.2 | 112 12856 128 | 1 12 1 | 2 22 2 |
| Conv3.1 Conv3.2 Conv3.3 | 56 256 28 256 28 256 | 1 1 1 1 2 1 | 4 4 4 4 4 4 |
| Conv4.1  Conv4.2  Conv4.3 | 28 512  28 512  28 512 | 1 1  1 1  1 1 | 8 8  8 8  8 8 |
| Conv5.1  Conv5.2  Conv5.3 | 28 512  28 512  28 512 | 1 2  1 2  1 2 | 8 16  8 16  8 16 |
| Conv6.1  Conv6.2  Conb6.3 | 28 512  28 512  28 512 | 1 1  1 1  1 1 | 8 16  8 16  8 16 |
| Conv7.1  Conv7.2  Conb7.3 | 28 256  28 256  28 256 | 1 1  1 1  1 1 | 8 8  8 8  8 8 |
| Conv8.1  Conv8.2  Conb8.3 | 56 128  56 128  56 128 | 1 1  1 1  1 1 | 4 4  4 4  4 4 |

Here X represents the spatial resolution of output, C represents number of channels of output, S represents the computation stride, D represents kernel dilation, Sa represents the accumulated stride across all preceding layers and De represents the effective dilation of the layer with respect to the input.

* 1. RESULT and DISCUSSION

In this section we are going to present the outcome of our research with validation. The proposed model has been trained and tested with the ImageNet dataset. That is publically available dataset. At the time of training and testing a total of 10k image data has been used. In this research we have also tested the some of the legacy black and white image. Further we have made validated the proposed method with the survey with independent user. The sample output of the image Net dataset is given in Table 2.

Table 2: The comparative result of the proposed model with original and ground truth image.

|  |  |
| --- | --- |
| Input-1 |  |
| Proposed Model Output |  |
| Ground Truth |  |
| Input-2 |  |
| Proposed Model Output |  |
| Ground Truth |  |
| Input-3 |  |
| Proposed Model Output |  |
| Ground Truth |  |
| Input-4 |  |
| Proposed Model output |  |
| Ground Truth |  |
| Input - 5 |  |
| Proposed Model Output |  |
| Ground Truth |  |

From the table 2 we can conclude that the proposed method colorization is almost near to the ground truth images. We have tested the model accuracy and achieved a total of 85.47% accuracy. To validate the proposed model we have colorized some legacy black & white image (source ImageNet dataset) and conducted an online survey with local pears and got 65% confidence. The legacy image colorization output is shown in Table 3.

Table 3: Proposed model output on Legacy Black and White images

|  |  |
| --- | --- |
| Input-1 |  |
| Proposed Model Output |  |
| Input -2 |  |
| Proposed Model Output |  |
| Input -3 |  |
| Proposed Model Output |  |
| Input - 4 |  |
| Proposed Method Output |  |
| Input - 5 |  |
| Proposed Model Output |  |

Table 3 shows the outcome of the legacy black and white images. For further validation we have tested our proposed model with man-made objects (source-ImageNet) and found most of the cases we did not reached to the original quality. The man-made object colorization is shown in table 4.

Table 4: Proposed model outcome is based on man-made images.

|  |  |
| --- | --- |
| Input-1 |  |
| Proposed model output |  |
| Ground Truth |  |
| Input-2 |  |
| Proposed Model Output |  |
| Ground Truth |  |
| Input - 3 |  |
| Proposed Method Output |  |
| Ground Truth |  |
| Input - 4 |  |
| Proposed Method Output |  |
| Ground Truth |  |

From the above tables table 1, 2 and 3, we can conclude that the proposed method is quite suitable for the natural image and legacy black and white images, but it is not suitable for the man-made objects.

To validate the proposed method we have compare the proposed method with the state of the art methods that used wide variety of the images. The comparison result shown in Table 5. From the table 5, we can conclude that the proposed method gives better result than others.

Table 5: Comparative result of the proposed method with state of the art methods.

|  |  |  |
| --- | --- | --- |
| Reference | Method used | Overall Accuracy |
| Zhou et al. (2014) [25] | ImageNet CNN feature+SVM | 68.5% |
| Wang et al. (2015) [26] | Places205-VGGNet-11 | 82.3% |
| Iizuka et al. (2016) [27] | CNN | 80.6% |
| Zhao et al. (2020) [28] | Deeplab-ResNet101 | 66.9% |
| **Proposed model** | **CNN+LAB color** | **85.47%** |

* 1. CONCLUSIONS

This research describes a unique, fully automatic colorization approach that use CNN to reduce human effort and enhance the image colorization as well as acceptability of the colorization. Image colorization is one method of adding style to a photograph or combining styles. Image colorization can also be used to add color to photographs that were previously black and white. In this proposed method the RGB color is converted into LAB color and then training and testing of the model is done. By training our model on ImageNet images dataset, we were able to get it to produce shots with realistic hues. Our method achieves 85.47% accuracy, requires fewer hand-tuned parameters and elements, and has been validated on a larger and more diversified set of test samples. Further our proposed method is implemented for legacy black and white images and for man-made images. The proposed model is quite suitable for natural image and legacy black and white image but not much suitable to colorize the man-made images. This research is limited to implementation of gray scale images, but several man-made images and black and white videos are also available required colorization.

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