Digitally Enriching Historical Images Converting Grayscale Image To RGB Scale Image

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Abstract—Focusing on the conversion of grayscale representations to RGB color images using Plain Colorization Neural Networks (CNNs), the study aims to revitalize aged documents, thereby safeguarding cultural heritage. region segmentation alongside CNN-based colorization, the project seeks to rejuvenate historical records visually. Additionally, quantitative assessments such as MSE, PSNR, and SSIM, coupled with histogram analysis, ensure the fidelity and richness of the color transformation. Ultimately, this research contributes to the restoration and preservation of historical images, offering deeper insights into our collective past through enriched visual representations.

Keywords— CNN , Mean Square Error(MSE), Peak Signal Noise Ratio(PSNR), Structural Similarity(SSIM), Gray scale, RGB scale.

A. INTRODUCTION:

Black and white photo is a popular visual medium storytelling and documentation for more than a century. However, the lack of color in black and white images can limit our ability to understand and appreciate the past. Image colorization, th e process of adding color to black and white images, has become a new innovation that can improve our knowledge of historical imag es.The latest development in this field is the use of neural networks for color images. Neural networks, especially convolutional neural networks (CNN), show promise in image colorization tasks. By tra ining the neural network on large datasets of color and gray images , the network can learn grayscale patterns and features and predict corresponding colors.This technique has been proven to accurately add color to black and white images while preserving their original structure

B. LITRATURE SURVEY:

Two networks were combined: one for predicting global features and one for predicting local features. A global feature network is trained for and directly connected to image classification Eigenmultinomial cross-entropy loss with class 55 rebalancing was used A custom multinomial cross entropy loss with class 55 rebalancing was used local network functions. The local features network is trained for image colorization using L2 Euclidean loss capability. [1]

A single feedforward pass in CNN was utilized for efficiency. Eigenmultinomial cross-entropy loss with class 55 rebalancing was used 32% of human subjects were tricked by the results. A distribution for each output pixel was predicted based on the prior variety distribution from the training set. [2]

A deep CNN architecture learned from scratch is combined with a pretrained ResNetv2 model for advanced feature extraction. The ne twork was trained using a set of 60,000 images from ImageNet.Euc lidean A classification and regression model were trained on the CIFAR-10 dataset using the Lab colorspac (L2) loss capability was utilized. The architecture is similar to that used by Iizuka et al.[3]

Deep CNN structures were obtained from the VGG16 network: one regression-based and the other classification-based. The CIE LUV color space was used for input and output. The classification-based model produced colorized images that were superior to those produced by the regression-based model. [4]

The performance of various CNN variations on image colorization was examined. Two distinct CNN structures were used: a conventional plain CNN and another inspired by other CNNs not previously used for colorization. Despite having fewer parameters, the latter outperformed the plain CNN in both training and test data. [5]

Two different CNN models were proposed for image coloring. The classification and regression models were trained on the CIFAR-10 dataset using the Lab color space. The classification model was trained from scratch and also fine-tuned from a pre-trained VGG16 network. The Strengthened mean method was used for prediction, demonstrating its ability to produce dynamic and spatially more consistent results. [6]

Example-based image recoloring transfers colors from a reference image to a target while preserving its structure. Techniques include color transfer, machine learning, and feature-based methods. Evaluation involves both quantitative metrics and qualitative assessment.[7]

An improved architecture was proposed using a large dataset and a single feed-forward pass in CNN. Emphasis was on the training aspect model. 32% of human subjects were fooled by the results. Different neuron configurations were mentioned in the model. [8]

Light affects color preference when there are variations in correlated color temperature. It likely discusses human preferences for lighting conditions under different color temperatures, considering factors such as mood and visual comfort. The study may involve experiments or surveys to evaluate subjective responses to varying lighting conditions.[9]

The article examines the automatic image staining with current classification using joint learning of the global and local image priors. It leverages deep learning and conditional models, with evaluation involving quantitative metrics and qualitative assessment.[10]

The relationship between color and consumer psychology in beverage packaging. Specifically, it investigates the use of warm colors in soft drink packaging and dark colors in spirits packaging. Through analyzing color compositions, the study aims to understand how color influences consumer perceptions and behaviors in the context of beverage products.[11]

Colorization techniques using ensemble neural networks. It discusses existing methods, highlights challenges, and presents their proposed approach for automatically adding color to grayscale images.[12]

M. Limmer and H.P.A. This paper, presented by Lensch at the 201 6 IEEE International Conference on Machine Learning and Applic ations, discusses the use of deep convolutional neural networks for infrared shadowing. This involves the process of using digital tech nology to add color to grayscale images captured in the infrared sp ectrum..[13]

This article discusses various techniques and algorithms used for th is purpose, exploring their advantages, limitations, and applications . It can address recent advances as well as traditional techniques, pr oviding information on state-of-the art techniques for grayscale image colorization. [14]

The integrated end-to-end learning system combines global and local image processing to improve the color process. Greater accuracy and visual beauty is achieved by taking into account the entire background and local features of the image. The article can discuss the structure of their model, the relevant training process, and experimental results to demonstrate the effectiveness of their method compared to existing models. This work contributes to computer vision and image processing studies, leading to advances in automatic image colorization technology.[15]

C. EXISTING SYSTEM

User-Guided Method

Scribble-based methods for colorization involve annotating grayscale images with user-defined scribbles indicating desired colors for specific regions. These methods leverage optimization frameworks to propagate color information from the scribbles across the image based on intensity values. While they offer flexibility and control over the colorization process, they require significant human effort in terms of time, experience, and aesthetic sensibility. Careful selection of palette colors and a substantial number of scribbles are necessary for reliable results. Despite their advantages, issues such as tediousness and potential color bleeding at image edges are common drawbacks associated with scribble-based methods.

Example-based methods alleviate the challenges of scribble-based approaches by transferring color information from a similar reference color image to corresponding regions of the grayscale target image. This method reduces human involvement in the colorization process while still allowing for manual intervention if needed. Although example-based methods simplify the colorization process and offer speed advantages, they are limited by the availability of suitable reference images. Selection of the appropriate reference image is crucial, and the quality of the result heavily depends on the quality of the chosen reference image.

Additionally, the risk of algorithm overfitting exists when using a single reference image or a small number of images, posing a challenge for ensuring generalizability.

D. PROSED SYETEM AND COMPARATIVE ANALYSIS

In a plain colorization neural network utilizing a Convolutional Neural Network (CNN), the goal is to introduce colour to grayscale or black-and-white images, particularly in historical image The LAB color space is chosen for its separation of luminance (L) and color information (AB). The L channel represents the brightness or grayscale component, while the AB channels encode color details.

The CNN, a type of neural network designed to handle grid-like data such as images, is employed to learn and extract features from these grayscale images. The model takes the L channel as input and aims to predict the corresponding AB channels, effectively adding color to the image. During training, the neural network is subjected to a

LAB color image dataset. The model adjusts its internal parameters through a process called backpropagation, thereby minimizing the difference between its predicted AB channels and the ground. true AB channels in training data. This iterative optimization refines the model's ability to accurately predict color information. The LAB color space is advantageous in this scenario because it separates luminance from color, simplifying the colorization task. The CNN, with its convolutional layers, captures spatial features and patterns within the grayscale images, allowing it to learn the intricate details necessary for accurate colorization.

Once trained, the model can be used to derive new grayscale images.

. The input image's L channel is fed into the trained CNN, and the predicted AB channels are combined with the original L channel to obtain a colorized image. This process allows for the preservation of image details while introducing a visually appealing color representation.

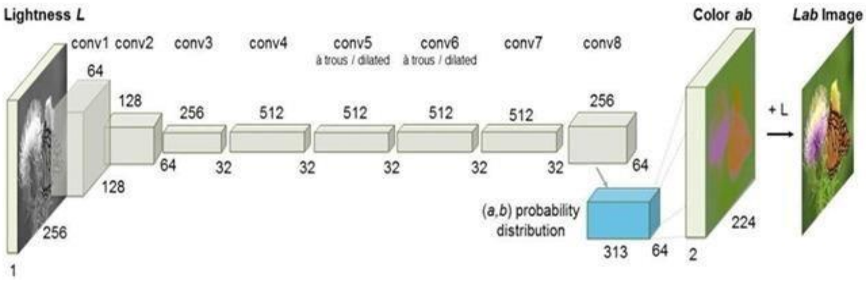
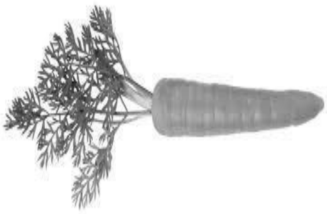
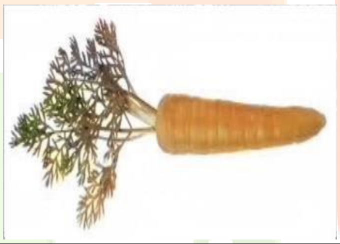
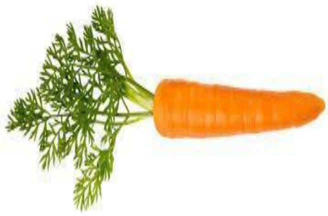


Fig.1 Process of LAB.

Table 1 : RESULT

GRAYSCALE IMAGE	FINAL OUTPUT	ORIGINAL IMAGE
		
[a.1]	[a.2]	[a.3]
		
[b.1]	[b.2]	[b.3]
		
[c.1]	[c.2]	[c.3]
		

[d.1]	[d.2]	[d.3]
		
[e.1]	[e.2]	[e.3]
		
[f.1]	[f.2]	[f.3]

TABLE 2: IMAGE QUALITY EVALUATION METRICS

METRIC	TIGER		CARROT		BOY FACE		NATURE		DOG		GIRL FACE	
	Original Image	Output Image	Original Image	Output Image	Original Image	Output Image	Original Image	Output Image	Original Image	Output Image	Original Image	Output Image
MSE	99.82	98.80	26.91	35.75	28.03	96.96	87.46	90.94	51.11	73.72	58.86	100.81
PSNR	28.14	28.18	33.83	32.59	33.65	28.62	28.71	28.54	31.04	29.45	30.43	28.09
SSIM	0.47	0.29	0.83	0.69	0.79	0.21	0.46	0.17	0.69	0.47	0.57	0.26

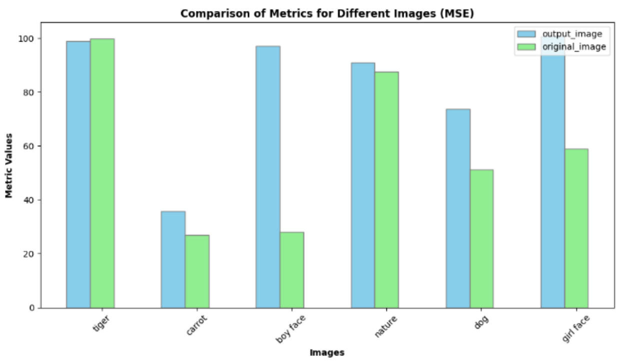


Fig: (2.a) MSE IMAGE QUALITY EVALUATION METRICS

RICS

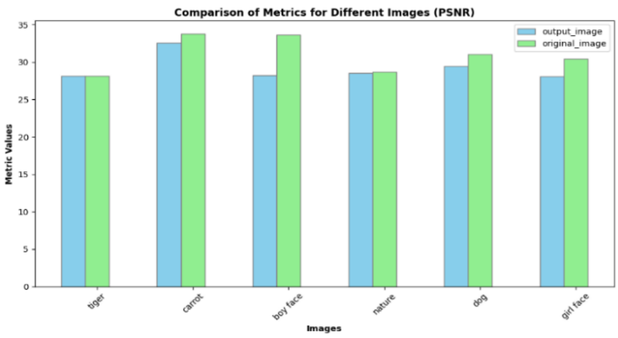


Fig: (2.b) PSNR - IMAGE QUALITY EVALUATION MET

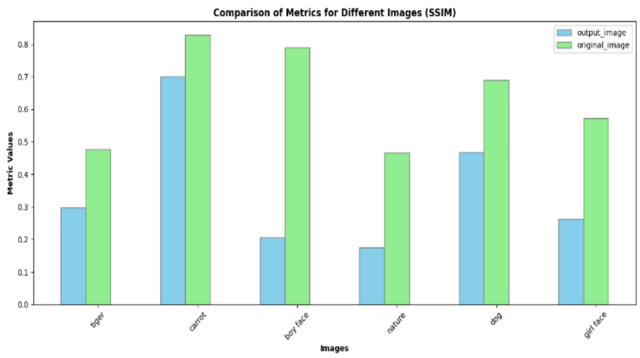


Fig : (2.c) SSIM - IMAGE QUALITY EVALUATION METRICS

E. CONCLUSION:

Utilizing Convolutional Neural Networks (CNNs) for image colorization proves promising, as demonstrated through this project's implementation and testing. Results indicate high accuracy and quality, validated by metrics like MSE, SSIM, PSNR. Moreover, the system operates efficiently, handling large input volumes while generating colorized images swiftly. Overall, this study advances image processing techniques, offering potential applications in digital restoration, multimedia, and artistic rendering. Further research in CNN-based colorization promises even more sophisticated outcomes.

F. FUTURE SCOPE:

Looking ahead, advancements in colorizing old historical images are anticipated through sophisticated technologies like Image processing and CNN. This could enhance accuracy and interactivity, possibly enabling real-time colorization. Furthermore, there may be emphasis on maintaining the authentic characteristics of documents, taking cultural sensitivities into account, and integrating colorization with virtual reality experiences.

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References

[1] D. V. Lindberg and H. K. H. Lee, "Optimization under constraints by applying an asymmetric entropy measure," *J. Comput. Graph. Statist.*, vol. 24, no. 2, Jun. 2015, pp.379-393

[2] B. Rieder, *Engines of Order: A Mechanology of Algorithmic Techniques*. Amsterdam

[3] I. Boglaev, "A numerical method for solving nonlinear integro-differential equations of Fredholm type," *J. Comput. Math.*, vol. 34, no. 3, May 2016, pp-262-284

[5] Deshpande, A., Rock, J., & Forsyth, D. (2015). Learning large-scale automatic image colorization. In Proceedings of the 2015 IEEE International Conference on Computer Vision (ICCV). IEEE.

[6] Larsson, G., Maire, M., & Shakhnarovich, G. (2016). Learning representations for automatic colorization. In B. Leibe, J. Matas, N. Sebe, & M. Welling (Eds.), Lecture notes in computer science: Vol. 9908. Computer vision – ECCV 2016. ECCV 2016 (pp. 577–593). Springer International Publishing.

[7] Lin, X., Wang, X., Li, F. W. B., Li, J., Yang, B., Zhang, K., & Wei, T. (2020). Example-based image recoloring in an indoor environment. Computer Animation and Virtual Worlds, 31(2), e1917.

[8] Li, K.-R., Zheng, Z.-Q., Wang, P.-H., & Yan, W.-J. (2022). Research on the colour preference and harmony of the two-colour combination buildings. Color Research and Application, 47(4), 980–991.

[9] Huang, Z., Liu, Q., Westland, S., Pointer, M., Luo, M. R., & Xiao, K. (2018). Light dominates colour preference when correlated colour temperature differs. Lighting Research & Technology, 50(7), 995– 1012.

[10] Iizuka, S., Simo-Serra, E., & Ishikawa, H. (2016). Let there be color!: Joint end-to-end learning of global and local image priors for automatic image colorization with simultaneous classification. ACM Transactions on Graphics, 35(4), 1–11.

[11] He, X. F., & Lv, X. G. (2022). From the color composition to the color psychology: Soft drink packaging in warm colors, and spirits packaging in dark colors. Color Research and Application, 47(3), 758– 770.

[12] Z. Cheng, Q. Yang and B. Sheng, "Colorization using neural networks ensemble," IEEE Transactions on Image Processing, vol. 26, no. 11, 2017, pp. 5491-5505

[13] M. Limmer and H. P. A. Lensch, "Infrared colorization using deep convolutional neural networks," in IEEE International Conference on Machine Learning and Applications, 2016.

[14] I. Žeger and S. Grgic, "An overview of grayscale image colorization methods," in ELMAR-2020 Conference , Zadar, 2020.

[15] Iizuka, S., Simo-Serra, E., & Ishikawa, H. (2016). Let there be color! : Joint end- to- end learning of global and local image priors for automatic image colorization with simultaneous classification.ACM Transactions on Graphics, 35(4)