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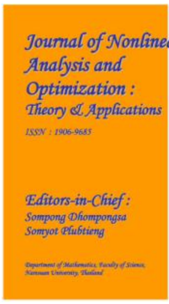

ENHANCING VISUAL DEPTH THROUGH ENERGY EFFICIENCY: GRAYSCALE IMAGE RESTORATION AND FULL SATURATION CONVERSION

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ABSTRACT: This project focuses on enhancing the visual quality of black and white landscape images through a combination of image denoising and colorization techniques using deep learning. Leveraging state-of-the-art Convolutional Neural Networks (CNNs) and advanced image processing algorithms, the work aims to remove noise artifacts from grey scale images and add realistic colors to create vibrant and visually appealing renditions. This project utilizes a dataset comprising of 1000 landscape images, each initially in black and white and of size 160 x160 pixels. To simulate real-world conditions, noise is artificially introduced into these images.. The de-noising aspect of the task involves techniques tailored for this purpose, while the colorization task employs a custom-designed CNN model architecture. The system architecture encompasses modules for data pre-processing, model training, evaluation, and deployment, ensuring seamless integration and efficient processing of landscape images. By leveraging cutting-edge technologies such as TensorFlow, Keras, OpenCV, and GPU acceleration, this work aims to deliver robust, scalable, and visually stunning solutions for landscape photography enhancement, pushing the boundaries of image processing and deep learning in the realm of landscape photography. Through meticulous experimentation and validation, we demonstrate the efficacy and practicality of our approach in producing high-quality colorized landscape images with reduced noise, thereby offering a valuable tool for photographers and enthusiasts in the field of landscape photography.

Keywords: image colorization, de-noising, encoding, decoding

1. INTRODUCTION

In today's digital era, images serve as a fundamental medium for conveying information, documenting events, and expressing creativity. However, images captured under real-world conditions often suffer from various imperfections, such as noise, artifacts, and lack of color information. These imperfections not only degrade the visual quality of images but also hinder their interpretability and usability in downstream tasks.

The purpose of this project is to address these challenges by exploring advanced image processing techniques, specifically focusing on two key tasks: image de-noising and colorization. Image de-noising aims to remove unwanted noise from images, thereby enhancing their clarity and sharpness. On the other hand, colorization involves inferring realistic colors for grayscale images, transforming them into visually appealing and informative representations.

Image restoration refers to the process of enhancing the quality of a digital image that has been degraded by factors such as blur, noise, compression artifacts, or other forms of distortion. The goal of image restoration is to improve the visual appearance of an image by reversing or compensating for these degradations, thereby making it more suitable for analysis or presentation.

A fully saturated image refers to an image where the colors are at their maximum intensity or purity. In the RGB color model, which is commonly used in digital images, saturation refers to the intensity of the colors. A fully saturated image would mean that each pixel in the image has the maximum possible intensity for its respective color components (red, green, and blue).

The motivation behind this project lies in the critical importance of image restoration and colorization in enhancing the visual quality and interpretability of digital images. The colorization of historical photographs can provide valuable insights into the past, enriching cultural heritage preservation efforts.

2. REVIEW OF LITERATURE

- H. Kim et. al. [28] describes the solution for the obstacles of color consistency distortion of images shared with near infrared region. His work captures textures in objects preserving color consistency.
- Y. Xiao et. al. [26] recommends a color theme method on grey scale images to choose colors by users and provide colorization to the image through deep neural networks. The results exhibit higher image quality for the same compression ratios.
- Min Wu et.al.[27] proposes a new model that is sensing image colorization method based on DCGAN it not only retains the largest image features but also can adjust the channel weights in the training process.
- S. Zaware et.al.[23]proposes an approach to fully automate the task using auto-encoder model. CNN is used because of its ability to deal with images and image processing. It is very efficient and beats the state of art technique in terms of accuracy.
- Althbaity et.al.[22] transforms monochrome photos into full color remains challenging despite high-resolution advancements. Current methods like Adobe Photoshop and MATLAB demand extensive time and expertise for effective colorization. A proposed algorithm leveraging image processing and deep learning aims to efficiently add color to monochrome photos, potentially extending to videos in the future.
- R. S. Shankar et.al.[21] proposed novel method for Image Colorization, vital in various fields like astronomy and surveillance, utilizes deep learning algorithms for automation. The paper

employs Convolutional Neural Networks (CNNs) and features Google's Inception ResNet V2 for efficient feature extraction. Through analysis of epochs and steps per epoch, optimal performance is achieved.

- Cheng, Z et. al. [18] delves into the theory and practice of deep colorization, highlighting the advancements made in this field. It discuss various methodologies within deep learning frameworks used for colorization, providing insights into the techniques employed.
- Cheng,Z et.al.[19] enhances the accuracy and efficiency of colorization processes through their proposed approach, potentially improving upon traditional methods.
- L. Kiani, et.al.[24] developed new approach that predicts multiple color results for grayscale pixels, especially in noisy environments, remains a significant challenge in automatic image colorization. The article proposes hypercolumns, leveraging semantic information and recent advancements in deep neural networks for accurate color prediction.
- Olaf Ronneberger et.al[30] presents us different techinques that help in data augmentation. The architecture enables us to extract context with precise localization. It performs better than existing methods only with help of very few images. It helps in the understanding of U-Net architecture.

3. PROPOSED SYSTEM

Colorization systems encounter several hurdles that impede their effectiveness and practicality. They often struggle with noise in input grey scale images, which can significantly diminish colorization quality and exacerbate noise amplification problems, ultimately leading to suboptimal results. Moreover, the computational demands of many colorization methods pose a considerable challenge, requiring substantial time and resources for both training and inference. This complexity limits their applicability, particularly in real-time or resource-constrained scenarios, hindering their widespread adoption and practical use.

Secondly, the variability in user interaction requirements further complicates the usability of colorization systems. While some systems aim to be fully automatic, others may necessitate manual intervention or user guidance to achieve satisfactory results, which can be time-consuming and tedious. Additionally, the high-end system requirements, including powerful CPUs, GPUs, and ample RAM, present a significant financial burden for individuals or organizations with limited budgets, further limiting accessibility. These challenges underscore the pressing need for advancements in colorization technology to address these limitations, improve usability, and enhance accessibility for a broader range of users.

A. Proposed system U-Net architecture

The proposed system aims to integrate image de-noising and colorization into a single framework using a U-Net-inspired architecture. This analysis will focus on the system's design, components, and performance evaluation.

U-Net Architecture: U-Net is a convolutional neural network architecture commonly used for semantic segmentation tasks, particularly in biomedical image analysis. It consists of a contracting path to capture context and a symmetric expanding path for precise localization. This architecture is highly effective for tasks where accurate delineation of structures or objects in images is crucial, such as colorization of black and white images.

B. **Algorithm (Pseudo code)**

```
inputs = Input(shape=[160, 160, 3])
a1_layer = downsample(128, (3, 3), False)
a1 = Sequential(a1_layer)(inputs)
b1_layer = downsample(128, (3, 3), False)
b1 = Sequential(b1_layer)(a1)
c1_layer = downsample(256, (3, 3), True)
c1 = Sequential(c1_layer)(b1)
d1_layer = downsample(512, (3, 3), True)
d1 = Sequential(d1_layer)(c1)
e1_layer = downsample(512, (3, 3), True)
e1 = Sequential(e1_layer)(d1)
a2_layers = upsample(512, (3, 3), False)
a2 = Sequential(a2_layers)(e1)
a2_concat = Concatenate()([a2, d1])
b2_layers = upsample(256, (3, 3), False)
b2 = Sequential(b2_layers)(a2_concat)
b2_concat = Concatenate()([b2, c1])
c2_layers = upsample(128, (3, 3), False)
c2 = Sequential(c2_layers)(b2_concat)
c2_concat = Concatenate()([c2, b1])
d2_layers = upsample(128, (3, 3), False)
d2 = Sequential(d2_layers)(c2_concat)
d2_concat = Concatenate()([d2, a1])
e2_layers = upsample(3, (3, 3), False)
e2 = Sequential(e2_layers)(d2_concat)
output_layer = Conv2D(3, (2, 2), strides=1, padding='same')
output = output_layer(e2)
```

C. **System Components**

Unified U-Net Architecture: The core of the system is the U-Net-inspired architecture, which combines both de-noising and colorization tasks.

Down-sampling Layers: Downsampling reduces the spatial dimensions and increases the number of channels in an image through convolutional operations. It extracts high-level features while discarding finegrained details, aiding in feature abstraction. Common downsampling techniques include convolutional layers with a stride greater than 1 and pooling layers.

Latent Space: Latent space refers to a lower-dimensional representation where complex data is encoded into a compact form. In deep learning, it represents the learned features or embedding extracted by a model. By capturing essential information, the latent space facilitates tasks like data generation, clustering, and interpolation.

Up-sampling Layers: Up-sampling increases the spatial dimensions and decreases the number of channels in an image through transposed convolutional operations. It aims to reconstruct high-resolution details from low-resolution feature maps, often used in image generation tasks like image super-resolution and semantic segmentation. Up-sampling layers help restore the original resolution lost during down-sampling.

D. Experimentation

This experiment is done using a dataset consisting of color and black and white images with noise and color degradation. The dataset consists of 1000 images of 160 x 160 pixels. Out of these 1000 images we consider training test ratio as 80% and 20%. Our work uses loss function as a measure to improve the colorization of the image. The loss function is calculated every iteration and our model is trained to reduce this loss function to gain more control on colorization. Our model converges if there is no significant change in the difference in loss function over several iterations. At this stage our model is said to learn the colorization aspects needed to convert the grey scale image to color image. The encoding process in our project involves extracting essential features from the input black and white landscape images. This is achieved through the application of convolutional layers, which convolve over the input images, capturing important patterns and structures. In contrast, the decoding process aims to reconstruct the original colorized images from the encoded representations obtained during encoding. This involves the utilization of up-sampling operations. By integrating contextual information, the decoder generates colorized images that closely resemble the original images. This helps the model to execute on machineries that possess low processing and computational powers. It makes our model energy efficient consuming less processing power. Our model best suits the application where computational powers are limited and restriction on usage of energy or processing power.

4. RESULTS

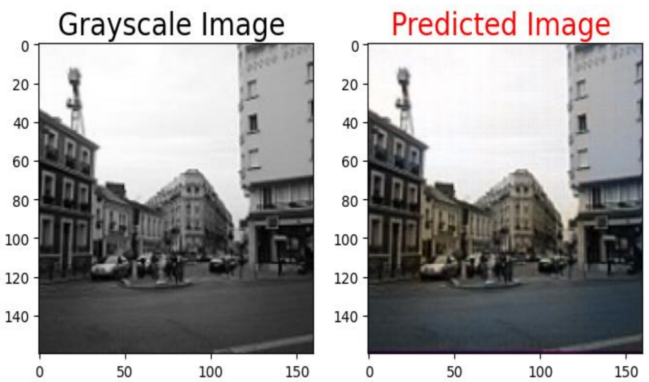

Fig1: The above figure illustrates the colorization of black and white image (left) to color image (right).

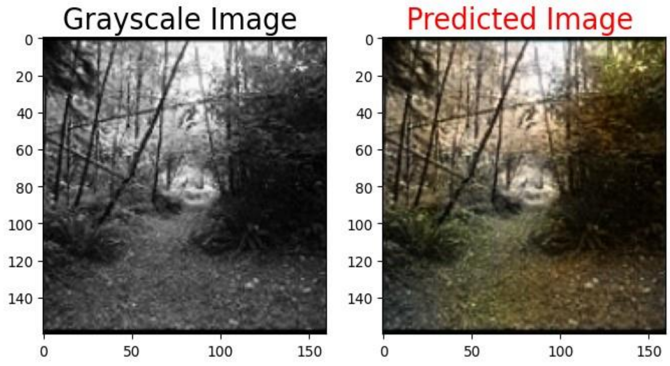

Fig 2: The above figure illustrates the colorization of black and white image (left) to color image (right).

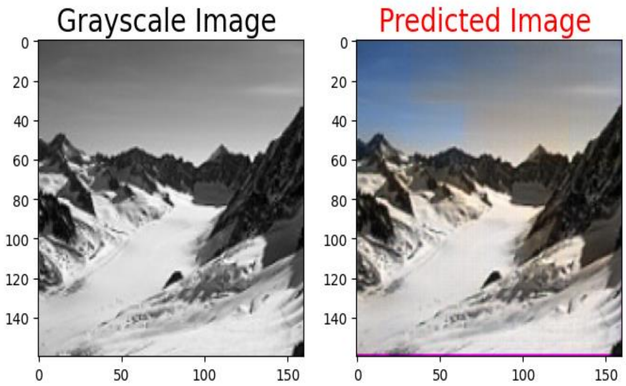

Fig 3: The above figure illustrates the colorization of black and white image (left) to color image (right).

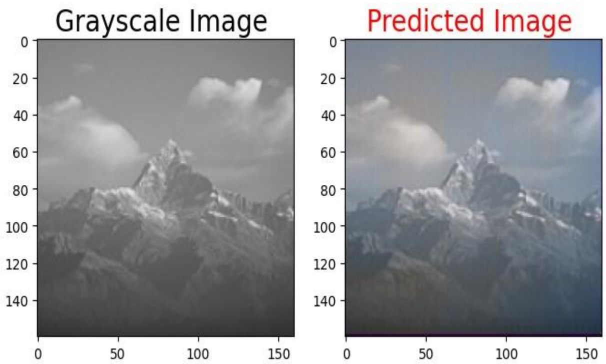

Fig 4: The above figure illustrates the colorization of black and white image (left) to color image (right).

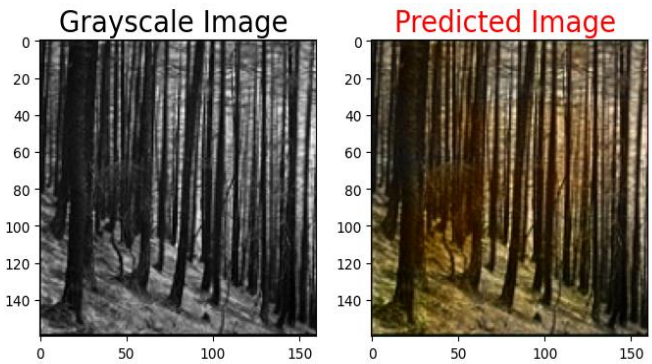

Fig 5: The above figure illustrates the colorization of black and white image (left) to color image (right).

5. CONCLUSION

In this project, we successfully tackled the tasks of image de-noising and colorization using deep learning techniques on a dataset comprising 1000 high-resolution landscape images. Through the implementation of a U-Net-inspired architecture, we trained a model capable of effectively removing noise from black and white images while preserving important spatial information. Additionally, we explored the challenge of colorizing these images, enhancing their visual appeal and realism.

The model demonstrated promising results in colorizing and de-noising, effectively removing artificial noise introduced to simulate real-world conditions and bring out fully saturated images. By leveraging skip connections, batch normalization, and activation functions, the model achieved significant noise reduction while maintaining the integrity of the landscape scenes.

Additionally, expanding the dataset to include a wider variety of landscape images and noise patterns could improve the model's generalization capabilities. Moreover, incorporating techniques such as data augmentation and adversarial training may enhance the model's robustness and ability to handle diverse environmental conditions.

However, this project has some limitations such as computational resources, dataset size and real world variations that occur. We have limited computational resources that prevented us from using a large dataset and advanced deep learning algorithms which in return affected the overall accuracy and efficiency of this project

REFERENCES:

1) Zhang, K., Zuo, W., Chen, Y., Meng, D., & Zhang, L. (2017). Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising. IEEE Transactions on Image Processing, 26(7), 3142-3155.

2) Lehtinen, J., Munkberg, J., Hasselgren, J., Laine, S., & Aila, T. (2018). Noise2Noise: Learning Image Restoration without Clean Data. Proceedings of the 35th International Conference on Machine Learning, PMLR 80, 2965-2974.

3) Anwar, S., Barnes, N., & Rajpoot, N. (2019). Real-world noisy image denoising: A new benchmark. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (pp. 0-0).

4) Tai, Y. W., Du, H., Brown, M. S., & Lin, S. (2017). Image Super-Resolution via Deep Recursive Residual Network. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 2790-2798).

5) Lefkimmiatis, S. (2018). Universal denoising networks: A novel CNN architecture for image denoising. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 3204-3213).

6) Xu, L., Ren, J., Liu, C., & Jia, J. (2018). DeepEdge: A Multi-Scale Bifurcated Deep Network for Top-Down Contour Detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 660-668).

7) Liu, G., Lin, Z., Shen, C., Reid, I., & Yan, S. (2015). Deep convolutional neural fields for depth estimation from a single image. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 5162-5170).

8) Xie, J., Xu, L., & Chen, E. (2012). Image Denoising and Inpainting with Deep Neural Networks. In Advances in Neural Information Processing Systems (pp. 341-349).

9) Dong, C., Loy, C. C., He, K., & Tang, X. (2016). Image Super-Resolution Using Deep Convolutional Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 38(2), 295-307.

10) Zhang, Y., Tian, Y., Kong, Y., Zhong, B., & Fu, Y. (2017). Residual Dense Network for Image Super-Resolution. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (pp. 2636-2644).

11) Zhang, R., Isola, P., & Efros, A. A. (2016). Colorful Image Colorization. In European Conference on Computer Vision (pp. 649-666). Springer, Cham.

12) Larsson, G., Maire, M., & Shakhnarovich, G. (2016). Learning representations for automatic colorization. In European Conference on Computer Vision (pp. 577-593). Springer, Cham.

13) 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), 110:1-110:11.

14) Deshpande, A., Rock, J., & Forsyth, D. (2015). Learning Large-Scale Automatic Image Colorization. In Proceedings of the IEEE International Conference on Computer Vision (pp. 567-575).

15) Charpiat, G., Hofmann, M., & Schölkopf, B. (2008). Automatic image colorization via multimodal predictions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 1-8).

16) 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), 110:1-110:11.

17) Zhang, R., Zhu, J. Y., Isola, P., Geng, X., Lin, A. S., Yu, T., & Efros, A. A. (2017). Real-Time User-Guided Image Colorization with Learned Deep Priors. ACM Transactions on Graphics, 36(4), 120:1-120:11.

18) Cheng, Z., Yang, Q., & Sheng, B. (2019). Deep Colorization: Theory and Practice. IEEE Transactions on Visualization and Computer Graphics, 25(5), 1821-1830.

19) Cheng, Z., Yang, Q., & Sheng, B. (2019). Colorful Image Colorization Using Convolutional Neural Networks. IEEE Access, 7, 158149-158160.

20) Deshpande, A., & Forsyth, D. A. (2015). Learning Large-Scale Automatic Image Colorization. In Proceedings of the IEEE International Conference on Computer Vision (pp. 567-575).

21) R.S. Shankar, G. Mahes, K.V.S.S. Murthy and D. Ravibabu, "A Novel approach for Gray Scale Image Colorization using Convolutional Neural Networks", *2020 International Conference on System Computation Automation and Networking (ICSCAN)*, pp. 1-8, 2020.

22) A. Althbaity, M. M. Dessouky and I. R. Khan, "Colorization Of Grayscale Images Using Deep Learning", *2022 14th International Conference on Computational Intelligence and Communication Networks (CICN)*, pp. 131-138, 2022.

23) S. Zaware, D. Pathak, V. Patil, G. Sangale and V. Gupta, "Gray Scale Image Colorization for Human Faces", *2021 International Conference on Design Innovations for 3Cs Compute Communicate Control (ICDI3C)*, pp. 107110, 2021.

24) L. Kiani, M. Saeed and H. Nezamabadi-Pour, "Image Colorization Using a Deep Transfer Learning", *2020 8th Iranian Joint Congress on Fuzzy and intelligent systems (CFIS)*, pp. 027-032, 2020.

25) S. Titus, "Fast Colorization of Grayscale Images by Convolutional Neural Network", *2018 International Conference on Circuits and Systems in Digital Enterprise Technology (ICCSDET)*, pp. 15, 2018.

26) Y. Xiao et al., "Interactive Deep Colorization and its Application for Image Compression", *IEEE Transactions on Visualization and Computer Graphics*, vol. 28, no. 3, pp. 1557-1572, March 2022.

27) M. Wu et al., "Remote Sensing Image Colorization Based on Multiscale SEnet GAN", *2019 12th International Congress on Image and Signal Processing BioMedical Engineering and Informatics (CISP-BMEI)*, pp. 1-6, 2019.

28) H. Kim, J. Kim and J. Kim, "Image-to-Image Translation for Near-Infrared Image Colorization", *2022 International Conference on Electronics Information and Communication (ICEIC)*, pp. 1-4, 2022.

29) Image Colorization with Deep Convolutional Neural Networks", *from Stanford.edu*, pp. 01-07, 2016.

30) Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015 (pp. 234-241). Springer, Cham.