

A Novel Method For Colorizing Black-And-White Videos And Images Utilising Faster R-CNN

LITERATURE SURVEY

[1] V. Pandit, R. Gulati, C. Singla and S. K. Singh, "DeepCap: A Deep Learning Model to Caption Black and White Images," 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2020

Colored picture captioning employs object identification and spatial connection to create captions. Few ways to captioning colourized photos exist. In this study, we caption B&W photographs without colorization. We utilised transfer learning to deploy Inception V3, a Google CNN model and runner-up in the ImageNet image classification competition, to produce captions from black-and-white photos with an accuracy of 45.7%.

[2] I. Žeger, S. Grgic, J. Vuković and G. Šišul, "Grayscale Image Colorization Methods: Overview and Evaluation," in IEEE Access, 2021.

Colorized grayscale photos. To prove result's authenticity. Grayscale photographs require colouring. In the past 20 years, numerous colorization systems have been created, from basic to complicated. Art meets AI in auto-conversion. This article discusses natural grayscale colorization. The study classifies colorization systems and discusses their pros and disadvantages. Deep learning. Image processing and quality. Image quality is measured in many ways. Human visual system complexity complicates picture quality assessment. Multiple colorization measures compare predicted and actual colour values, contradicting image believability. User-guided neural networks automate colorization with human input.

[3] D. Goel, S. Jain, D. Kumar Vishwakarma and A. Bansal, "Automatic Image Colorization using U-Net," 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), 2021

Automatic Image Colorization converts grayscale images to colourful images without human intervention. The major goal of the project is to create an automated method for colourizing grayscale images. Our U-Net architectural concept was presented. This challenge involves picture segmentation + multinomial classification. Results include chosen output photos. We supplied a black-and-white picture, our model's coloured output, and the ground truth.

[4] J. Yuan and Z. He, "Adversarial Dual Network Learning With Randomized Image Transform for Restoring Attacked Images," in IEEE Access, 2020.

Using adversarial dual network learning with randomised nonlinear image transform, we protect deep neural networks against assaults. We add a randomised nonlinear transform to disrupt attack noise. We build a generative cleaning network to recover damaged picture information and reduce attack noise. We also build a detector network to identify assault noise patterns for the defended target classifier. Using adversarial learning, the generative cleaning network and detector network battle to reduce perceptual and adversarial loss. Extensive experimental findings show that our technique enhances white-box and black-box assaults. It enhances white-box attack categorization accuracy by more than 30% on SVHN and 14% on CIFAR-10.

[5] Q. Yang, Y. Liu, T. Zhou, Y. Peng and Y. Tang, "3D Convolutional Neural Network for Hyperspectral Image Classification Using Generative Adversarial Network," 2020 13th International Conference on Intelligent Computation Technology and Automation (ICICTA), 2020

ML studies HSI classification. HSI captures light of multiple wavelengths. 3D hyperspectral data. We described domain adaptation technology, a well-established method for extending an algorithm learnt in one or more "source domains" to a different (but related) "target domain," and gave a 3D-CNN combined with GAN framework to handle unknown classes. Classify hyperspectral pictures appropriately. Our universal model has fewer training parameters and epochs than prior systems. Using Pavia University scene datasets, we study open-set adaption. The approach detects unknown categories 87.16% on PaviaU and 99.43% on Salinas.

[6] Q. Yang and Y. Fan, "An evaluation method of municipal pipeline cleaning effect based on image processing," 2022 3rd International Conference on Information Science, Parallel and Distributed Systems (ISPDS), 2022

Lack of pipeline-cleaning robots. New pipeline robot. Combining high-pressure water jet cleaning with the robot's underwater camera and image processing technology. Image processing and Python measure robot cleaning effect. Defogged, enhanced, segmented, and binarized pictures vividly show pipe size and wall. Black-to-white pixel ratio measures cleaning effect. This method can distinguish scale and pipe wall in a foggy image, according to tests. This examines the robot's performance.

[7] A. A. Polat, M. F. Şahin and M. E. Karsligil, "Video Colorizing with Automatic Reference Image Selection," 2021 29th Signal Processing and Communications Applications Conference (SIU), 2021

Coloring black-and-white films aims to make them perceptually relevant and aesthetically appealing. Old photographs from the past to the

present may be visualised and presented this manner. In this research, Convolutional Neural Networks colourize the footage. In this work, video frames are colourized using an autonomously derived reference picture. Instead of picking a reference picture for each frame, a system automatically recognises scene changes in the video stream and proposes the appropriate photo.

[8] X. Wang, C. Huang, F. Gao and H. Cheng, "Pre-processing Transformation for Enhancing the Transferability of Adversarial Examples," 2022 4th International Conference on Communications, Information System and Computer Engineering (CISCE), 2022

Adversarial instances that alter input images may misclassify deep neural networks. Most adversarial attack tactics are effective in white-box but not black-box. To construct adversarial examples, we describe the Shear & Pad Method (SPM). Reduces overfitting to improve adversarial example transferability. This technique may be used with others, such quick gradient sign method, to attack defense-trained models. It may be used with other transformation-based technologies to create transportable black-box enemies. Our strategy has a higher success rate than existing baseline attack techniques, according to ImageNet research. Our method evaluates deep network resilience.

[9] F. Woitschek and G. Schneider, "Online Black-Box Confidence Estimation of Deep Neural Networks," 2022 IEEE Intelligent Vehicles Symposium (IV), 2022

DNNs improve perception and planning in AD and ADAS. When inference data differs from training data, DNNs are brittle. In unexpected conditions, this hinders ADAS implementation. DNN standard confidence stays strong despite declining classification reliability. Motion control algorithms deem the confident prediction believable, even if it's wrong. Real-time confidence estimates must match DNN classification reliability to solve this problem. Integrating externally created components uniformly requires black-box confidence

evaluation. This article analyses this use case and proposes neighbourhood confidence (NHC). The metric simply requires the top-1 class output, not gradients, training datasets, or hold-out validation datasets. The NHC beats a comparable online white-box confidence estimate in low data regimes, which is critical for real-time AD/ADAS.

[10] K. Nimala, G. Geetha and J. G. Ponsam, "Colorization of Black & White Videos & Photographs," 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSSES), 2022

This paper predicts a grayscale picture's music. Previous methods prevented this. It may need input or have terrible colours. Brilliant, vivid colour is created automatically. Using a division function and class re-equation to training time enhances colour variation effect. CNN tests their technology with 1 million colour photographs. We test our algorithm by allowing people to pick between the truth and the base. In 32% of the survey, our strategy is more successful than others. Color is a multichannel motivator and learning connection. This modifies learning benchmarks.

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