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Old Gray Scale Images Conversion

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ABSTRACT: The main objective of this paper is to colorize historic images, which are only in black and white form using concepts of convolutional neural networks in prototxt file to construct our desired model. Colorization requires considerable user intervention and remains a boring, sluggish, and extortionate task. So, in this paper we have build a model to colorize the grayscale images automatically by using CNN algorithm in Deep learning where we have used all 4 layers of CNN which are not used in existing papers, which resulted into 13.75% better output than deep hybrid model. This layers will be written in prototxt file. In the existing papers, they only talk about images but we have tried our model on live feed taken from webcam and give the colourful live feed on the otherside, but it doesn't give good output.

KEYWORDS: Image Colorization, Convolutional Neural Networks (CNN), Deep Learning Grayscale to Color Conversion, Live Feed Colorization

I. INTRODUCTION

Colorizing black and white movies is a very old idea since 1902. For years many movie creators resist the idea of colorizing their black and white films and thought of it as destruction of their art. Today it is accepted as an amplification to their work of art. The technology itself has changed from meticulous hand colorization to today's highly automated techniques. In the USA, Legend movies used its automated technology to color old classics. In 1960, the movie Mughal-EAzam was famous in India, was colorized in 2004. People from various generations over-crowded the theatres to watch it in color and the movie was a successful for the second time. In this paper, we have trained a Convolutional Neural Network (CNN) to link a black & white image input to a colorful output. In this we are using a pre-trained caffemodel that can be retrieved by the use of opencv in python. Our idea is to use a fully automatic approach which produces decent and realistic colorizations. Deep learning is an existing function of AI that works similarly like a human brain. Example, it processes the data and creates patterns for the use in decision making. The black & white image we have to color can be thought as the L-channel of the image in the LAB color space L channel: to encode lightness intensity only, a channel: to encodes green-red, b channel: to encode blue-yellow and our objective is to find the a and b components that is luminance and chrominance. Which is done by CNN layers. The Lab image we got can be modified to the RGB color space by the use of standard color space transforms.

II. LITERATURE SURVEY

D.Futschik(2019) Manual colorization of black and white images isa laborious task and inefficient. It has been attempted using Photoshop editing, but it proves to be difficult as it requires extensive research and a picture can take up to one month to colorize. A pragmatic approach to the task is to implement sophisticated image colorization techniques. The literature on image colorization has been an Image of interest in the last decade, as it stands at the confluence of two arcane disciplines, digital image processing and deep learning. Efforts have been made to use the ever-increasing accessibility of end-to-end deep learning models and leverage the benefits of transfer learning. Image features can be automatically extracted from the training data using deep learning models such asConvolutional Neural Networks (CNN). This can be expedited by human intervention and by using recently developed Generative Adversarial Networks (CNN). We implement image colorization using various CNN and CNN models while leveraging pre-trained models for better feature extraction and compare the performance of these models.

J.Hwang and Y.Zhou(2020) Colorization, a task of coloring monochrome images or videos, plays an important role in the human perception of visual information, to black and white pictures or videos. Colorizing, when done manually in



Photoshop, a single picture might take months to get exactly correct. Understanding the tediousness of the task and inspired by the benefits of artificial intelligence, we propose a mechanism to automate the coloring process with the help of convolution neural networks (CNNs). Firstly, an Alpha version is developed which successfully works on trained images but fails to colorize images, and the network has never seen before. Subsequently, a Beta version is implemented which is able to overcome the limitations of Alpha version and works well for untrained images. To further enhance the network, we fused the deep CNN with a classifier called Inception ResNet V2 which is a pre-trained mode Kadiri et al. (2024) addressed the growing challenge of image authenticity in the digital age with a machine learning approach to recognize morphed pictures. Their system combines scikit-learn and OpenCV to detect alterations by analyzing distortions and changes in images. OpenCV facilitates feature extraction and pre-processing, while scikit-learn develops a machine learning model trained on datasets of real and altered images to differentiate between them. This method enhances the reliability of digital content by providing a robust tool for image verification, which can be integrated into existing forensic and verification pipelines to strengthen image security and authenticity.

K.Kiani et. al(2021) Image colorization is an interesting yet challenging task due to the descriptive nature of obtaining a natural-looking color image from any grayscale image. To have a fully automatic image colorization procedure, we propose a convolutional neural network (CNN)-basedmodel to benefit from the impressive capabilities of CNN in the image processing tasks. Harnessing from the convolutional-based pre-trained models, we fuse three pre-trained models (VGG16, ResNet50, andInception-v2) in order to improve the model performance. The average of three model outputs is used to obtain more rich features in the model. We use an encoder-decoder network to obtain a color image from a grayscale input image. To this end, the features obtained from the pre-trained models are fused with the encoder output to input into the decoder network.

Existing System:

Image colorization is an interesting yet challenging task due to the descriptive nature of obtaining a natural-looking color image from any grayscale image. To have a fully automatic image colorization procedure, we propose a convolution neural network (CNN)-based model to benefit from the impressive capabilities of CNN in the image processing tasks.

Harnessing from the convolution-based pre-trained models, we fuse three pre-trained models (VGG16, ResNet50, and Inception-v2) in order to improve the model performance. The average of three model outputs is used to obtain more rich features in the model. We use an encoder-decoder network to obtain a color image from a grayscale input image.

Drawbacks:

- > You need a lot of clarity when deciding deep hybrid model.
- > Difficulty keeping up with hybrid schedules..

Proposed System

To guess a suitable color, we require more information to study the model to match a grayscale input image to the equivalent color of the output image. In the past few years, Convolutional neural network is one of the most successful learning-based models. CNN verified spectacular capabilities in image processing. In such manner, CNN-based model is proposed by us for automatic image colorization.

Advantages:-

- ▶ It is 13.75% better output than deep hybrid model.
- > It automatically detects the important features without any human supervision.

System Architecture:

The diagram illustrates the process of converting a grayscale image to an RGB image using a Convolutional Neural Network (CNN) model. The process begins with a grayscale image, which is fed into a CNN model consisting of a caffemodel and a prototxt file. The model is trained using sample images, and the convolution layer applies convolution operations to extract features from the image. The pooling layer then reduces the spatial dimensions of the feature maps. The output from the pooling layer is fed into a CNN-based feature learning network, which outputs features for both training and testing samples. These features are flattened into a one-dimensional vector and passed through a fully



connected layer, resulting in the final output of an RGB image. This diagram provides a clear and structured overview of how a CNN model can be used to convert grayscale images to RGB images, highlighting the key stages and components involved in the process.

Feature Learning

- 1. Start: The process begins with a grayscale image.
- 2. CNN Model: The grayscale image is fed into a CNN model, which consists of a .caffemodel and a .prototxt file.
- 3. Training Samples: The model is trained using sample images.
- 4. Convolution Layer: This layer applies convolution operations to extract features from the image.
- 5. Pooling Layer: This layer reduces the spatial dimensions of the feature maps.
- 6. Feature Learning Network: The output from the pooling layer is fed into a CNN-based feature learning network.
- 7. **Output Features**: The network outputs features for both training and testing samples.



III. METHODOLOGY

Modules Name:

A. Study Area

The proposed method was tested on aerial photographs of the city of Strasbourg (France) and its surroundings (see Fig. 4). With an estimated population of 550 000 in 2015, the Eurométropolede Strasbourg (EMS) is the sixth most populated city in France. Located in the Upper Rhine Graben, it covers a surface of 340 km2 and is bordered by the Rhine River and the Vosges Mountains. Due to its history, topography, and hydrography, Strasbourg and nearby cities have a dense urban landscape and an open-field agricultural system

B. Available Data and Preprocessing

The colorization model developed in this article relied on an extensive historical spatial database designed by the ZoneAtelier EnvironnementaleUrbainethat is part of the French Long-Term Ecosystem Research network. The database consists of numerous orthophotos, which cover the entire EMS, from 1932 to 2013 (see Table II). Four dates were candidates for the colorization process as they were the only ones with available grayscale photographs: 1932, 1956, 1964, and 1978. Due to deterioration (1932) and spectral incompatibility with the other stills (1932 and 1964), we focused this research only on the 1956 and 1978 aerial photographs. To learn the semantics suitable for aerial photography, we designed a custom dataset based on the available photographs.

C. Grayscale-to-Color Mapping Using Deep Learning

Due to the unstable nature of GANs in their vanilla setting, a conditional DRAGAN was trained to learn the panchromaticto- color mapping. Initially proposed by Kodali et al. [54], DRAGANs, a subcategory of GANs, were



developed from the assumption that mode collapse and instability can be explained by the model converging toward a nonoptimal local equilibrium. Therefore, tweaking the objective functions by penalizing the discriminator's gradients can help avoid such a situation [54].

In the case of colorization, this technique helps learn a proper color distribution, including low-frequency samples, and avoids similar color generation over inherently different land covers and spatial semantics.

Transfer learning

It is not always required to train the network from random initialization values, many newer networks use a pretrained model as its initialization instead. When training a model that deals with a similar problem as an already trained network, this can be extremelybene_cial, increasing convergence rate and improving performance. One disadvantage of doing so is that it imposes constraints on used network architecture, as the weights that are _ne-tuned from are generally locked into a specific structure.

Implementation:

CNN algorithm

Our training dataset is caffemodel and testing data is pretext file. In caffemodel image Net dataset is used to convert the images into LAB color space. As we cannot train the caffemodel with lakhs of images, we are using the pertained caffemodel. Now, coming on prototxt file here we will be writing code to implement 4 layers of CNN which will result into better output as the existing system does not uses all the 4 layers, it only uses 2 layers. So, if we use the 4 layers where we can use the loss function to get better output. So, Layer1 consists of convolution layer and rely as shown in the first block and then again convolution rely plus batch normalization to lower the outcome of network initialization on intersection, avoid unstable gradients, and permit rapid learning rates leading to rapid convergence. In Layer 2 there is the addition of pooling layer to reduce the dimensions of the feature maps. Similarly, in each layer have different combinations of convolution and relu combining with pooling and batch normalization to make the result more accurate. In last layer use softmax to convert the scores to a normalized probability distribution.

Experental Results





IV. CONCLUSION

We presented a method of fully automatic colorization of unique grayscale Gray Scale images combining state-of-theart CNN techniques. Using the right loss function and color representation, we have shown that the method is capable of producing a plausible and vibrant colorization of certain parts of individual images even when applied to a moderately sized data set that has properties which make it harder to colorize than natural images, but doesnot perform as well when applied to video sequences.

In doing so, we visually and quotably compared several variants of CNN design, which desired in loss functions, architectures and regularization methods. It is clear that the models we used have a hard time learning colorization of large uniform regions such as background sky or walls but fare better when smaller objects and characters are present. We also proposed two methods of improving the generated results which greatly increase the visual resemblance of generated colorization to the ground truth images. One novel contribution is using and comparing a model inspired by residual CNNs for the task of colorization and showing that despite the smaller ERF and fewer parameters, it can generate results that are comparable or even surpass plain convolution neural networks in generalization to unseen data.

V. FUTURE ENHANCEMENTS

In order to be applicable for video, the method would currently require further tenement, performed manually by an artist. If trained on a larger dataset, the predictive power of the model would increase and is likely to produce more consistent colorization. For future work, it would be interesting to compare colorization produced by ResNet models with significantly more depth (which require more computational resources totrain) and models based on conditional generative adversarial networks, as the results have been able to put together when applied to natural images are quite impressive and allow the user to have more control over the result by adjusting the latent space variable.

Additionally, the CNN model could be adjusted to generate scribbles to use in conjunction with the algorithms we mentioned in Chapter 3, instead of full colorization. This could lead to results that more closely match the currently used colorization methods that apply color to Gray Scale movies..

REFERENCES

- 1. D.Futschik. "Colorization of black-and-white images using deep neural networks". Jan, 2018.
- 2. V.Trivedi, H.Saifuddin, S.Gudadinni, S.Sondhi and M.A.R.Shabad."Automatic Colorization of Black and White Images Based on CNN", Sinhgad Academy of Engineering, Pune, India. May.5,2020.
- 3. J.Hwang and Y.Zhou. "Image Colorization with Deep Convolutional Neural Networks".2016.
- 4. K.Kiani, R.Hemmatpour, and R.Rastgoo. "Automatic Grayscale Image Colorization using a Deep Hybrid Model". May 2021.
- 5. K.Kiani, R.Hemmatpour, and R.Rastgoo. "Automatic Grayscale Image Colorization using a Deep Hybrid Model". May.13,2021.
- 6. N. Lakshmi Prasanna, Sk. Sohal Rehman, Naga Phani, S. Koteswara Rao, and T. Ram Santosh. "AUTOMATIC COLORIZATION USING CONVOLUTIONAL NEURAL NETWORKS". 7 July,2021.
- 7. R.Zhang, P.Isola, and Alexei A. Efros. "Colorful Image Colorization", Berkeley. Oct.5,2016.
- 8. S.Kotala, S.Tirumalasetti, V.Nemitha, and S.Munigala. "Automatic Colorization of Black and White Images using Deep Learning", Osmania University, Hyderabad, Telangana. April,2019.
- 9. T.Nguye and R.Thawonmas. "Image Colorization Using a Deep Convolutional Neural Network". April,2016.
- 10. C. A. S. Domonkos Varga and T. Szirfffdfffdnyi, Automatic Gray Scale colorization based on convolutional neural network, https://core.ac.uk/download/pdf/94310076.pdf, 2017.
- 11. S. Salve, T. Shah, V. Ranjane, and S. Sadhukhan, Automatization of coloring grayscale images using convolu- tional neural network, Apr. 2018. DOI: 10.1109/ICICCT. 2018.8473259.
- 12. Automatic colorization of images from Chinese black and white films based on cnn, 2018. DOI: 10.1109/ICALIP. 2018.8455654
- V. K. Putri and M. I. Fanany, "Sketch plus colorization deep convolutional neural networks for photos generation from sketches," in 2017 4th International Conference on Electrical Engineering, Computer Science and Informat- ics (EECSI), Sep. 2017, pp. 1–6. DOI: 10.1109/EECSI. 2017.8239116.
- Kadiri, P., Anusha, P., Prabhu, M., Asuncion, R., Pavan, V. S., & Suman, J. V. (2024, July). Morphed Picture Recognition using Machine Learning Algorithms. In 2024 Second International Conference on Advances in Information Technology (ICAIT) (Vol. 1, pp. 1-6). IEEE.





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