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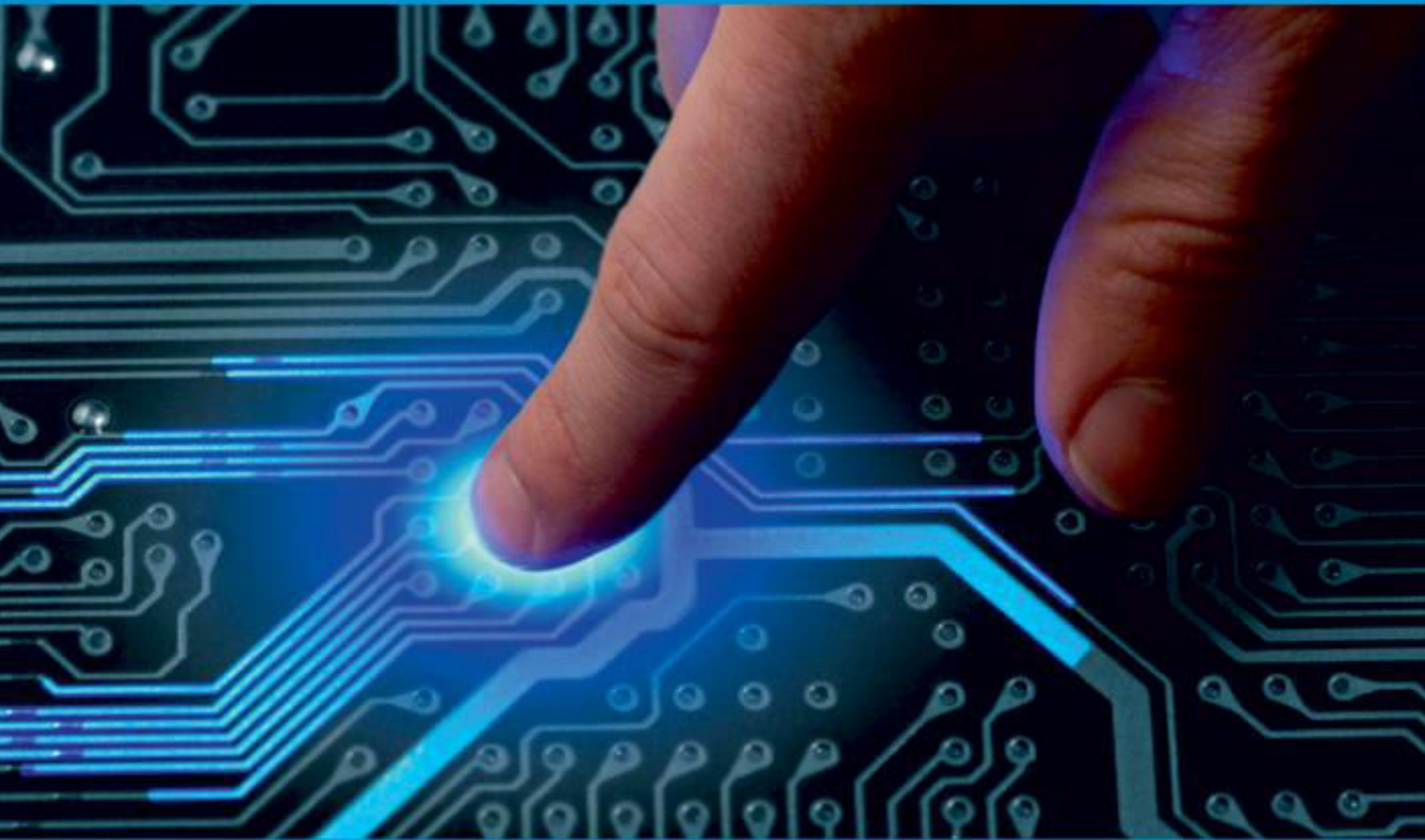

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Enhance Image Using Deep Learning

Shaik Asif Ur Rehman[1], Tellagorla Purna Chandra Rao[2], Vadranam Danny Victor Joshi[3,]

K. Thrilochana Devi[4]

UG Student, IV Year Dept. of I.T., Vasireddy Venkatadri Institute of Technology, Guntur, India[1]

UG Student, IV Year Dept. of I.T., Vasireddy Venkatadri Institute of Technology, Guntur, India[2]

UG Student, IV Year Dept. of I.T., Vasireddy Venkatadri Institute of Technology, Guntur, India[3]

Assistant Professor, Department of Information Technology, Vasireddy Venkatadri Institute of Technology, Guntur, India[4]

ABSTRACT: The major goal of our paper is to provide an overview of how the colorization problem can be utilised to turn a grayscale image into a colourful image and then used to colour a video. To obtain artifact-free quality, this usually necessitates manual reconciliation and is thus regarded as a difficult challenge. The procedure usually necessitates a careful selection of colourful allusion images.In contrast to previous methods, this work intends to develop a high-quality totally autonomous colorization method and to apply it to images obtained from video sequences. The recent advances in deep learning approaches are the basis for this article, which focuses on reformulating the colorization problem such that we may use deep learning approaches quickly and apply this methodology to videos. Our method is a completely automated procedure. To the best of our knowledge, no current articles or research studies address the topic of employing deep learning techniques to colourize films.

KEYWORDS: Image Colorization; Deep Learning; Convolution Neural Networks(CNN); Color Segmentation; Image Classification

I. INTRODUCTION

Machine Learning is a branch of technology with vast capabilities and applications for automating processes that do not require human participation or explicit programming. We can see ML's applications trending nearly everywhere in our day-to-day lives, such is its potency. Many previously unsolved problems have been solved via machine learning, and the world's enterprises have advanced significantly. Deep Learning is a subset of machine learning that is essentially a three-layer neural network that powers many artificial intelligence (AI) applications and services in computer science.

A new technical paradigm, such as 3D modelling or auto-colorization, provides a fascinating aesthetic appearance in addition to the ancient procedures that were employed to conserve historical images. Due to technological restrictions, only black and white photographs were available when photography was initially established. Color photography, on the other hand, has become a way of life in recent years. With historical photography, there are many recollections and links between the present and the past. Converting them to coloured ones would be more intriguing for improving hidden meanings and visual appeal.

Manual painting or Photoshop were the methods of colorization, and both were time demanding. Wall paintings, fabric paintings, and manuscripts are all examples of Nepalese painting, which has been practised for millennia.The process may now be carried out automatically thanks to artificial intelligence (AI) and deep learning. Given a gray-scale historical, heritage, or cultural input photograph. The purpose of this study is to create an auto-colorized image using a deep convolutional neural network technique (CNN).

II. LITERATURE SURVEY

Ryan Dahl's CNN-based approach for automatically colourizing photos inspired our project. His system is based on several layers of ImageNet-trained from VGG16 that will be integrating with a system that is an auto encoder with residual connections that aid in merging intermediate outputs generated by the encoding part of the network, which includes the VGG16 layers, with those generated by the later decoding part of the network[3]. The ResNet system developed by He et al., which won the 2015 ImageNet challenge, was the inspiration for the residual connections.Because the connections are utilised to connect upstream and downstream network edges, they allow for more rapid doorgifte of gradients with the help of the system, reducing training convergence time and enabling more reliably in training deeper networks. Dahl reports that, as compared to a previous model that couldn't use residual

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connections, his most current approach reduces training loss on each training iteration on a considerably greater scale. According to the findings, Dahl's method performs exceptionally well in terms of realism[8]. Nonetheless, we notice that the system's visuals are mostly sepia-toned and subdued in colour in many cases.Dahl formulates picture colorization as a regression issue, but the training goal to be reduced is the sum of Euclidean distances between each pixel in the target and predicted images that are blurred colour channel values. While regression appears to be well suited to the task because it demonstrates the continuous nature of colour spaces, a classification-based technique may be more practical.Consider a pixel in a flower petal that appears in numerous photos that are identical except for the colour of the flower petals. The captured pixel can have a variety of tones or hues, including red, yellow, blue, and many others. The value of the projected pixel minimises the loss for this particular pixel is the mean pixel value in a regression-based system that uses a '2 loss function. As a result, the anticipated pixel is an unappealing, subdued blend of the various colours or tones.Consider a pixel in a flower petal that appears in numerous photos that are identical except for the colour of the flower petals. The captured pixel can have a variety of tones or hues, including red, yellow, blue, and many others. The value of the projected pixel minimises the loss for this particular pixel is the mean pixel value in a regression-based system that uses a '2 loss function. As a result, the anticipated pixel is an unappealing, subdued blend of the various colours or tones.Considering this scenario, we hypothesise that a regression-based system would tend to generate images that are desaturated and impure in colour tonality, especially for objects that take on many colours in the real world, and that this is the reason for the lack of punchiness in colour in Dahl's system's colourizedimages[10].

III. PROPOSED SYSTEM

Mostly to ensure the change in color or adding color to the images by using different types of algorithms but they all differ in different functionalities and also the vivid results of colorization of the image decided accordingly with type of algorithm used. We designed a deep learning neural network that gives machines the ability to make inferences about our results accordingly measured by the mean square value and the accuracy levels of our training model.

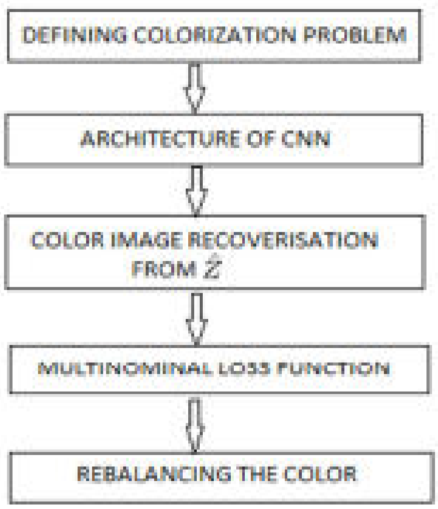

Fig. 1 Proposed flow of the methodology

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A. *The colorization problem:*

There are two approaches to define the colorization problem: RGB colour space and CIE colourspace.Black and white images can be described as grids of pixels in RGB colour space, with each pixel's value ranging from 0 to 255, with 0 being black and 255 denoting white. The brightness of a pixel is determined by its values.

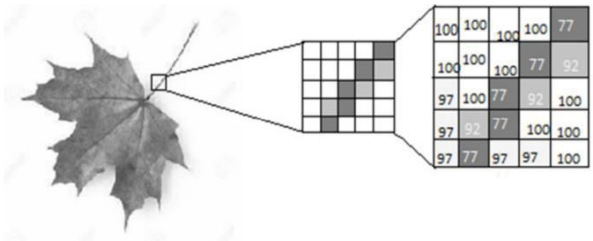

Fig. 2 Pixel Representation

Ared layer, a green layer, and a blue layer are the three layers that a RGB color images generally consist. For example, consider a green leaf that is split into three channels on a white background. One may think that the leaf is present only in the green channel but as shown in the below diagram, the leaf is present in all the 3 channels of a RGB color space, which determines the brightness along with the color.

Fig. 3 Presence of an image in all three channels of a RGB color space

B. *CNN Architecture for Enhancement:*

Zhang et al. proposed a VGG-style network with several convolutional blocks as the design of CNN. Each block is made up of three layers: two or three internal convolutional layers in the first section, a Rectified Linear Unit (ReLU) in the second layer, and a Batch Normalization layer in the third. There are no pooling layers in this architecture.

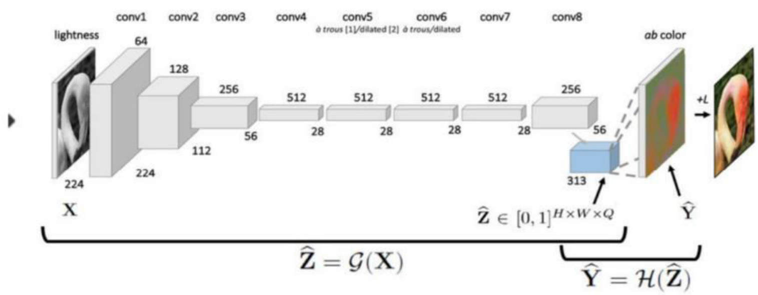

Figure: Design Architecture of CNN

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Let's call the input image 'X.' X should be a rescaled image of 224x224 pixels. X is turned into 'Z' after passing through the neural network described above. This transformation is denoted by the letter 'G,' and can be written mathematically as:

- Z^ = G(X)

The dimensions of Z are HxWxQ, where H(=56) and W(=56) are the height and width of the output produced in the last convolution layer, respectively. For each HxW pixel, Z comprises a vector of Q(=313) values. Q is a number that represents the likelihood of a pixel belonging to that class. For each probability distribution Zh,w, the purpose of our paper is to determine a single pair of ab channel values.

C. *Color image recoverisation from Z^ :*

- The above-mentioned graphic depicts a group of distributions in Z derived from the scaled input image X. From each distribution in Z, we must now retrieve a single ab value pair. We could just take the distribution's mean and choose the ab pair that corresponds to the quantized bin centre closest to us. The resulting distribution is not Gaussian, i.e., the mean corresponds to an unnaturally desaturatedcolour. Consider the colour of the sky, which might be blue or orange,yellow depending on the season. The distribution of sky hues is bimodal. While colouring the sky with either blue or yellow results in grey, colouring the sky with the average of blue and yellow results in grey.
- We can use the mode of the distribution to produce either a blue or yellow sky to get brilliant colours, although this breaks the spatial consistency occasionally. The solution is to interpolate between the mean and mode estimations to obtain the annealed-mean quantity. Temperature(T) was used as a control parameter for the interpolation degree. As a compromise between the two extremes, T=0.38 is adopted as the final number. In Yh,w, which can be described as a transformation of the original distribution Zh,w, the ab pair corresponding to the annealed-mean of the distribution Zh,w is represented.
  - Y = H(Z)
- It is a mathematical expression that expresses the relationship between two variables. The predicted ab image, Y, has the same dimension as the picture flowing through the CNN, which is 56*56. To create the final colour image, it is upsampled to the original image size and then added to the lightness channel, L.

D. *Feature Extraction:*

- Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. It yields better results than applying machine learning directly to the raw data.

E .*Classification Model:*

- Classification is a process of categorizing a given set of data into classes, It can be performed on both structured and unstructured data. The process starts with predicting the class of given data points. The classes are often referred to as target, label, or categories.
- The classification predictive modeling is the task of approximating the mapping function from input variables to discrete output variables. The main goal is to identify which class/category the new data will fall into.

Classification Algorithms can be further divided into the Mainly two categories:

- Linear Models
  - Logistic Regression
- Non-Linear Model

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- Decision Tree Classification

F .*Block Diagram and Architecture Diagram of CNN*:

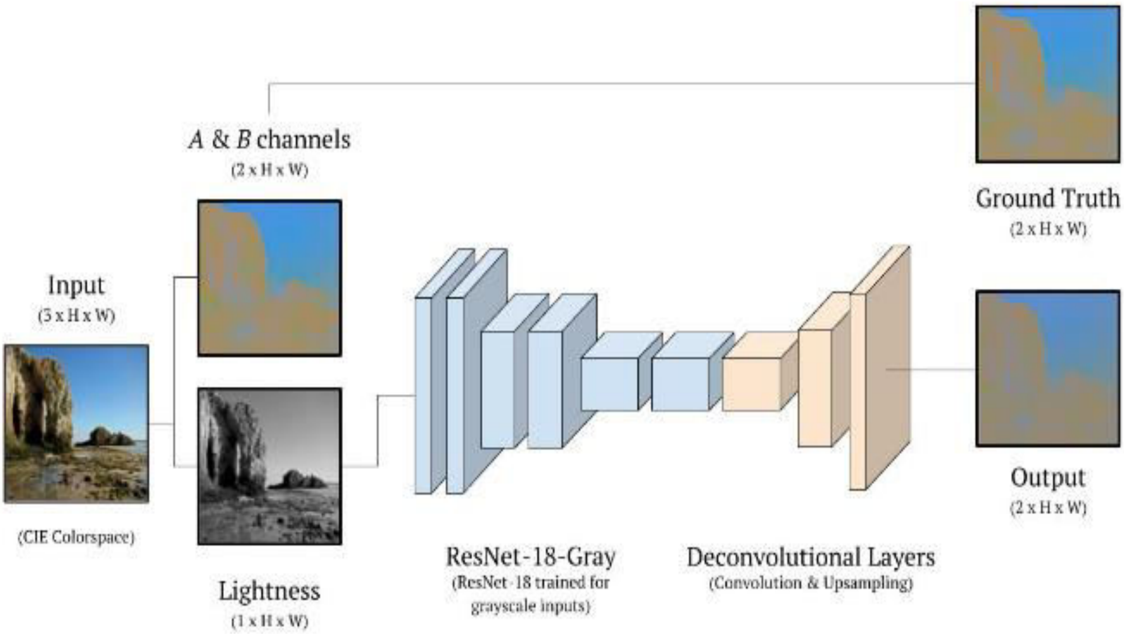

Figure :Block Diagram

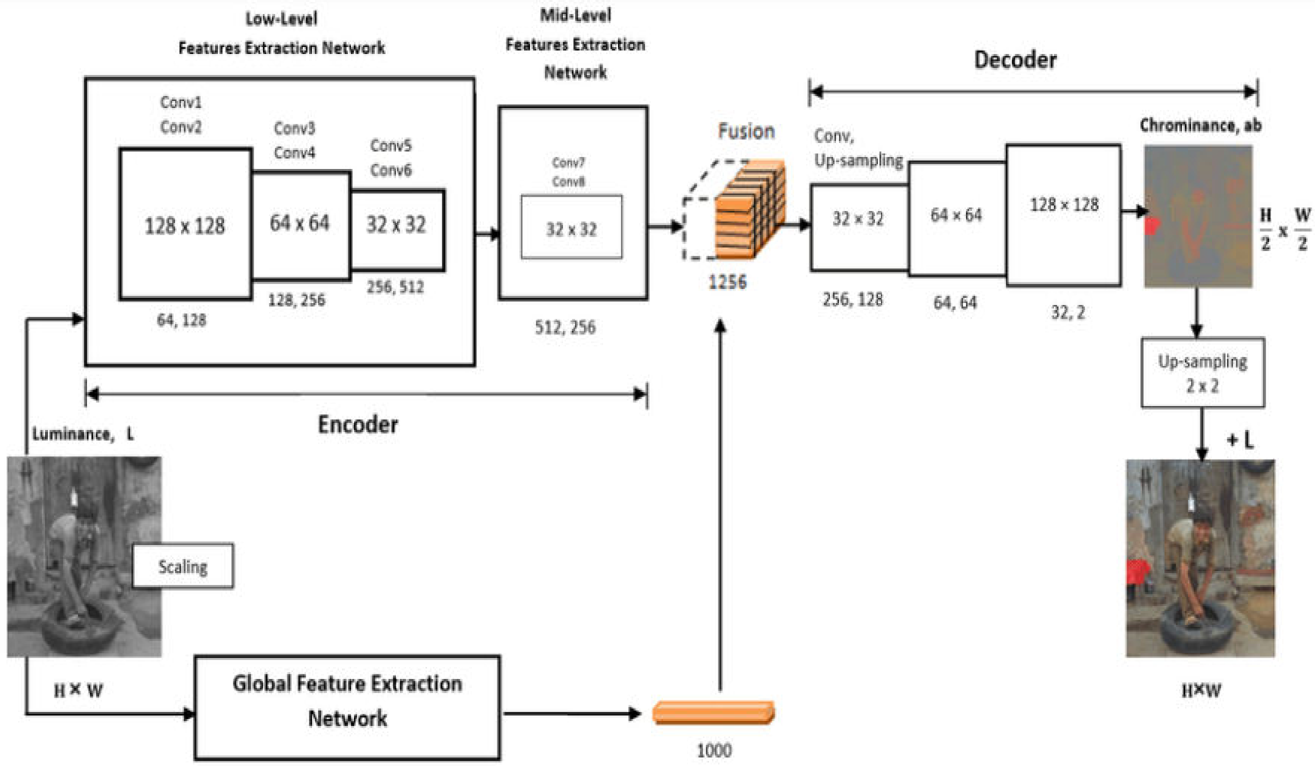

Figure :Flow of the Proposed System

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V. RESULTS & DISCUSSION

The suggested enhanced deep learning method was compared to existing techniques, as shown in the diagram below, which shows two sets of regression and classification network outputs, as well as their black-and-white input photos. The MIT CVCL Open Country dataset was used to train the model that generated these photos.

Figure: Process Enhancement of images

The outputs of the regression network appear to be reasonable. Green tones are limited to sections of the image with greenery, while the sky appears to have a minor colour tinting. The photos, on the other hand, are highly desaturated and unappealing in general. Given their resemblance to Dahl's sample outputs and our theory, these results are to be expected

A. Sample Result when tested gray scale images:

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B. A single-gray scale image validation

VI. CONCLUSION AND FUTURE WORK

We have proved the efficacy and promise of utilising deep convolutional neural networks to colourize black and white photographs through our research. We've shown that framing the challenge as a classification problem can result in colourized photos that are arguably far more aesthetically beautiful than those produced by a baseline regression-based algorithm, and so holds a lot of promise for future improvement. As a result, our work creates a firm platform for future endeavours. As we move forward, we've found a number of ways to improve our present system. To address the problem of colour inconsistency, we can use segmentation to enforce colour homogeneity inside segments. To obtain a comparable result, we can use post-processing approaches like total variation minimization and conditional random fields. Finally, building the system around an adversarial network could produce better results, because instead of focusing on minimising cross-entropy loss per pixel, the system would learn to generate images that are comparable to real-world images. The network we planned and created would be a prime contender for being the generator in such an adversarial network based on the quality of results we've achieved.

REFERENCES

1. Iizuka, Satoshi, Edgar Simo-Serra, and Hiroshi Ishikawa. "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 (TOG) 35.4 (2016): 110.
2. Cheng, Zezhou, Qingxiong Yang, and Bin Sheng. "Deep colorization." Proceedings of the IEEE International Conference on Computer Vision. 2015.
3. Larsson, Gustav, Michael Maire, and Gregory Shakhnarovich. "Learning representations for automatic colorization." European Conference on Computer Vision. Springer, Cham, 2016.
4. Li, Bo, et al. "Depth and surface normal estimation from monocular images using regression on deep features and hierarchical CRFs." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2015.
5. Zhang, Richard, et al. "Real-time user-guided image colorization with learned deep priors." arXiv preprint arXiv:1705.02999 (2017).
6. Deshpande, Aditya, Jason Rock, and David Forsyth. "Learning large-scale automatic image colorization." Proceedings of the IEEE International Conference on Computer Vision. 2015.
7. Limmer, Matthias, and Hendrik PA Lensch. "Infrared colorization using deep convolutional neural networks." Machine Learning and Applications (ICMLA), 2016 15th IEEE International Conference on. IEEE, 2016.
8. Deshpande, Aditya, Jason Rock, and David Forsyth. "Learning large-scale automatic image colorization." Proceedings of the IEEE International Conference on Computer Vision. 2015.
9. C. Dong, C. C. Loy, K. He, and X. Tang. Learning a deep convolutional network for image super resolution. In ECCV, pages 184–199. Springer, 2014.

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