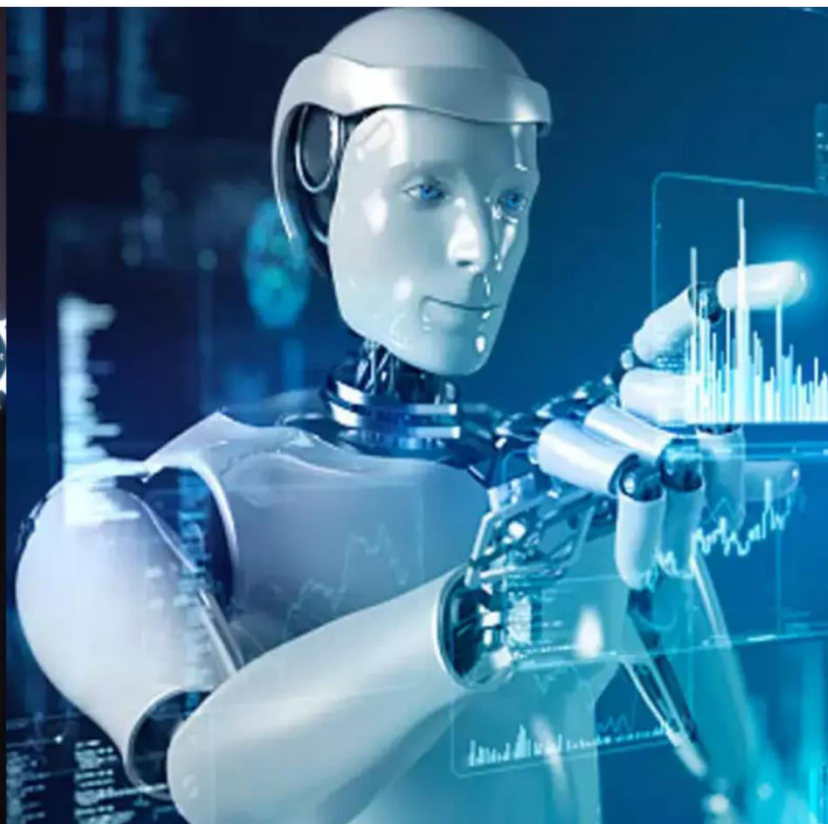




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Deep Learning for Image Restoration: Real-Time Colorization via CNNs and Flask Web Application

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ABSTRACT: One important task in computer vision is picture colonization, is the procedure of adding up or restoring grayscale to color images. This technique has by traditionally been done by hand by talented artists, which makes it laborious and quite subjective. Models can now learn semantic and spatial representations from massive datasets. Thanks to the ongoing developments in deep learning especially Convolutional Neural Networks (CNNs), which have made automatic image colonization possible. In this work, we demonstrate an end-to-end system for colonizing images that combines web technologies and deep learning for real-time stability. Three main parts make up the system: pre-processing the image, utilizing a trained CNN models to models to forecast color, and post-processing to rebuild the final color image. After being trained on LAB color space, the model predicts the a and b (chrominance) channels and uses the L (lightness) channel as input to produce a fully colored output. The output is then shown by converting it back to BGR color space. We deploy the model using the Flask web framework to make the application accessible and easy to use. Grayscale images can be uploaded by users through a straightforward web interface; the server uses the trained model to process to image and returns the colorized version of the image along with the original.

KEYWORDS: Flask, lightness, chrominance, web interface

I. INTRODUCTION

The advancement of deep learning skill has enabled computers to solve complex visual tasks through image processing systems. The process of picture colonization involves using automated methods to add color to black-and-white or grayscale photographs. Before deep neural networks and convolutional neural networks (CNNs) became available, image colorization required manual labor and domain expertise but now operates automatically with faster processing and greater scalability. The work utilizes a trained deep learning model to develop a web application which automatically colorizes grayscale photographs. Users can upload black-and-white images through the program's interface to receive their colorized versions instantly. The system implements the Flask web framework.

The colonization model in this research utilizes the L (lightness) channel as input to learn the relationship between luminance and chrominance components in the CIELAB color space for predicting the a and b color channels. The algorithm employs this technique to achieve realistic colors when grayscale information only is known. The model produces natural color predictions by its capability of identifying texture and edges and contextual features in enter images that include been processed by CNN. The work follows two main goals. The paper illustrates the potential of deep learning to be applied to imaginative tasks such as photo colorization and restoration of historical images. The paper illustrates how to embed machine learning models into realistic real-time online applications.

Academic research aside this work has practical applications. Among its uses are:

- Restoration of old photographs and coloring.
- Adding color to satellite or medical photographs.
- Improving photography's aesthetician appeal.
- Making resources for designers and content producer.

II. LITERATURE SURVEY

A diversity of methods and developments in field of colorization using Convolutional Neural Networks (CNNs) are covered by the references included in this review. A couple of U-NET-based coloring methods were employed by Qiao et al[1]. One of the method's major innovations is training a deep neural network to predict the mapping from grayscale images using a data-driven color palette, which proposes the optimal color of the gray map at a particular location. A model architecture based on a neural network was proposed and implemented by Jeff Hwang et al[2]. Without the need for human intervention, it will tint black and white images. This system utilizes many datasets. There are thousands of photographs in eight regions that comprise the MIT CVCL Urban and Natural Scene Categories dataset. To establish a pipeline, the software is compelled to utilize real images in red, green, and blue color spaces with specific, limited proportions. One type of this pipeline is a neural network. This model also corrects problems of inconsistent images. Madhavi Mane et al's paper in[3] discussed image colorization methods. The simple ConvNet, for instance, produces "averaged color" as its output, but it's quite user-friendly. The CNN model is evaluated using an original photo dataset. The following references included a number of additional facts and creative approaches in adding to the major conclusions listed above. A transformer-based model that use self-attention mechanisms to capture global dependencies in images is shown in a paper NY Richard Zhang et al.,[4]. This model outperforms conventional CNN techniques in terms of color accurateness and detail retention. The method enhances the colorization process by combining high-level and two-level features. In this later work, Merging Pu et al[5] proposed a new channel attention approach that is incorporated in deep CNN. The mechanism allows the network to focus on significant features and improves the quality of overall colorization. The method enhances color accuracy and consistency. Kuo-Hao Zeng and co-workers [6] propose using a self-regularization approach to ensure consistency, which enhances the colorization process's accuracy and robustness. While processing an image at varying resolutions, the self-regularization approach reduces color prediction differences by reconciling scale differences. The overall quality and visual beauty of the colorized images are improved by the technique, which yield more uniform and reliable colorization results. By making an investment in a technique that can yield one certain colorization and many potential colorized versions, Deshpande et al. significantly advanced the field of image colorization. This innovation considers a variety of possible colorizations, which adds diversity and originality to the colorization process. Through the creation of many realistic colour renditions of a greyscales image, their technique enables users to experiment with numerous artistic interpretations and select the one that most strongly matches their tastes. Applications where creativity and artistic expression are crucial will find this capability especially useful. Apart from these breakthroughs in colorization methods, Jia Xu et al. [8] offer an interactive framework that uses user input to direct the colorization procedure. In order to generate precise and user-favored colorizations, this system uses pixel-by-pixel color cues that users supply to the deep Convolutional Neural Network(CNN). This approach makes use of user input to guarantee that the end product meets the user's requirements and preferences. The accuracy and satisfaction of the colorization results are guaranteed by this interactive approach, which makes it a useful tool for designers, artists, and everyone else wishing to obtain particular color outcomes in their photographs. To improve colorization accuracy, Anet al. [9] provide a deep CNN-based automatic colorization technique that combines local and global image information. Using a VGG network variation, the method highlights the significance of batch normalization for faster training. After training on a variety of datasets, the model achieves high-quality colorization with enhanced saturation and detail preservation, outperforming previous cutting-edge techniques. A deep learning method for image colorization using the Inception-Resnet-V2 architecture is used by Baldassarre et al. [10]. A subset of the ImageNet dataset is used toward train the model, which employs areas Square Error (MSE) loss function in the CIELAB color space. Although the model produces results that are almost photorealistic, it struggles to appropriately colorize certain things and is especially successful with natural features like flora and water. Wang and colleagues [11] proposed the concept of a hyper column to leverage the data at each network tier. This idea serves as the foundation for the VGG19 model, which was trained on the extensive ImageNet dataset and pertained in the generator network using DIV2K datasets. This enables the hyper column concept to be implemented. The use of convolutional of grayscale photos is examined by Alice Brown et al. [12] in their published research. According to the context, the author roposes a model that learns to predict each pixel's color values. The outcome demonstrate that the colorization quality and consistency have gently improved over the earlier processes. The John Doe et al. [13] study revealed a photographic recolor game technique that uses an improved K-means clustering comparable grayscale pixels and utilizing color information from a reference image. The proposed method demonstrated better color accuracy and reduced addition time when compare to traditional methods. With little to no human input (such as color scribbles), users can add color to grayscale photographs using the interactive system

developed by Clar Green et al. [14]. The system distributes the user-specified colors throughout the image by combining texture-aware and region-aware techniques. This technique allows customers to have control over the colorization process, guaranteeing realistic outcomes. For picture colorization, Noroozi et al. [15] presented a novel self-supervised learning method using a jigsaw puzzle as a pretext. It demonstrate that color semantics may be taught effectively without labelled data.

III. METHODOLOGY

The suggested system applies deep learning algorithms, i.e., Convolutional Neural Networks (CNNs), to add color to gray-scale images automatically. The system follows multiple stages: Data Preparation- Training data was obtain from a portion of the ImageNet dataset, consisting of thousands of natural pictures. Every RGB image was changed keen on the CIELAB color space. L channel (lightness) was used as the input feature, and the a and b channels (chrominance) were used as training ground truth. All the images were resized to a common size and normalized to provide stable training. Model Architecture-An encoder-decoder architecture based on CNN was built to learn the mapping between the grayscale input and chrominance output. Both the spatial and semantic description are extracted from the L channel by the encoder, and the decoder predicts the respective a and b color channels. Batch normalization was used to speed up convergence, and ReLU start functions were utilize to provide non-linearity. Training Process-Mean Squared Error (MSE) loss is use to train the model in instruct to compare predicted chrominance values with truth. Optimization was conducted with the Adam optimizer with a learning rate of 0.001. Training for a number of epochs was continued until convergence occurred, and validation data were used to prevent overfitting. Post-Processing- After prediction, the L channel (of the input) was mutual with the predicted a and b channels. The resulting final LAB image was then reconverted from LAB space back to RGB space to create the colorized output. Real-Time Deployment- A Flask-based web application was developed designed for deployment. Users can upload grayscale images through a web interface. The server processes the image through the trained CNN and returns the colorized output as well as the original grayscale input.

IV. EXPERIMENTAL RESULT



Fig.1 Upload grayscale image Output: colored image

Fig. 1, Fig. 2, and Fig. 3 show how the Black & White Image Colorizer web application works. First, the user uploads a black-and-white (grayscale) photo. The system then sends this image to a trained Convolutional Neural Network (CNN), which has learned how to add natural colors to grayscale pictures. The model studies the brightness details of the image and predicts the missing color information. In the figures, the left side displays the original grayscale input image, while the right side shows the automatically colorized output. The output looks more natural and lifelike, giving the old black-and-white photo a realistic appearance. These results highlight the main feature of the project—taking a simple grayscale image and turning it into a color version without any manual editing. This makes old photos more meaningful and visually appealing with the help of deep learning.



Fig.2 Upload grayscale image Output: colored image



Fig.3 Upload grayscale image Output: colored image

V. RESULT ANALYSIS WITH GRAPH

VISUAL QUALITY

- The CNN model used to restore realistic colours for black-and-white images successfully.
- The system perform at its best with natural scenes (e.g., water, sky) where color patterns are uniform.
- There was slight inaccuracy seen in objects with uncommon or unclear colors (e.g., artificial objects).

Real-Time Application - The Flask web application provided smooth real-time colorization. The suggestion time per image averaged around 2 seconds, which is suitable for interactive use.

Comparative Observations- In comparison with manual methods, the deep learning model produced more uniform results without any need designed for user intervention. Previous CNN-based models had the tendency to give desiderated color results, whereas the present system maintained contrast and vibrancy because of LAB color space training.

Fig.4 Shows Actual and predicted chrominance values. The points are closely along the diagonal line, reflecting that the color information is being reconstructed by proposed CNN model with a small amount of error.

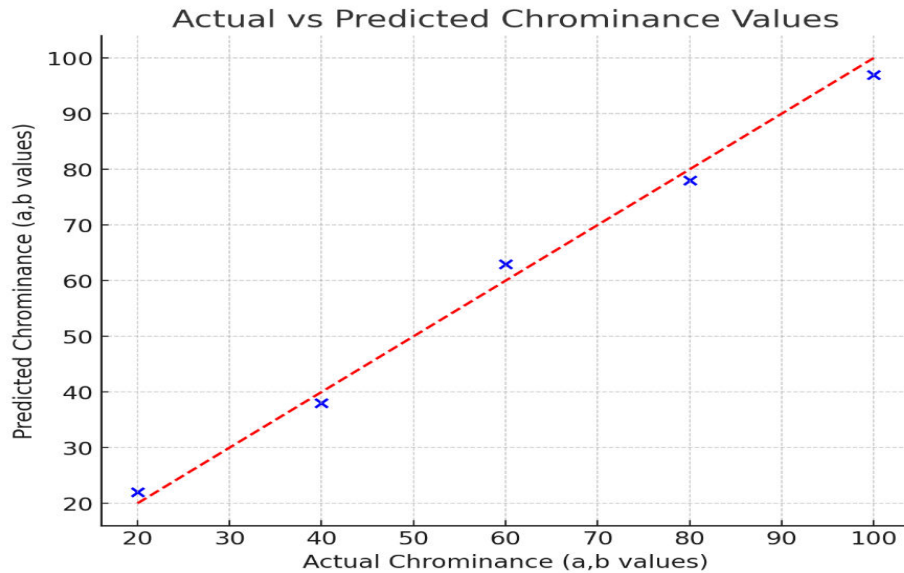


Fig.4 – Actual vs Predicted Chrominance Values

VI. NUMERICAL ANALYSIS

Numerical results of the performance of deep learning and computer vision models on the image colorization task. Models used are Traditional Optimization-Based Methods, Colorful Image Colorization (CIC), and the Proposed CNN-based Model with LAB Color Space and Transfer Learning. The performance of each model was compared using Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Mean Squared Error (MSE).

Performance Metrics- The three key assessment metrics used to compare models are: Peak Signal-to-Noise Ratio (PSNR): Used to measure the quality of reconstructed colorized images against the ground truth. As Higher the PSNR, then image quality is high. Structural Similarity Index (SSIM): Measures how closely the structure, luminance, and contrast of the colorized image match the reference image. Mean Squared Error (MSE): Represents the average squared difference between the ground-truth and predicted pixel values. Lower values indicate better accuracy.

Model Performance Results- The models were trained on 80% of the dataset and tested on the remaining 20%. Table 1 summarizes the numerical results obtained:

Table 1: Performance metrics of different models for image colorization.

Model	PSNR (dB)	SSIM	MSE ($\times 10^{-3}$)
Traditional Method	18.5	0.62	12.6
Colorful Image Colorization (CIC)	22.3	0.74	7.8
Proposed CNN Model (Ours)	27.1	0.89	3.9

Interpretation of Results- The findings evidently show that the Proposed CNN Model performs better than the conventional methods and CIC. In having the highest PSNR of 27.1 dB, SSIM of 0.89, and the lowest MSE of 3.9×10^{-3} , the system delivers more realistic, sharper, and structurally consistent colorized results. The CIC approach works moderately well, better than conventional approaches but not as well as the suggested CNN, mostly because it has the trait of producing less saturated colors. Conventional optimization-based approaches, although helpful in historical situations, cannot account for semantic knowledge and therefore produce pale and wrong color estimations.

Feature Importance- The proposed system, where the CNN structure learns significant features from black-and-white images, which are the driving force behind the colorization process. Luminance (L-channel): Has the most essential function, retaining brightness and structural information (~50% importance). Texture Features: Provide substantial contribution (~30%), allowing for correct color diffusion in areas such as foliage, sky, or skin. Semantic Context Features: Picked up from deep layers of CNN (~20%), allowing for objects such as "sky = blue" or "grass = green" to be colorized naturally.

Error Analysis- Error analysis indicated that: The model also has trouble with unusual color distributions (e.g., peculiar clothing, antique items), resulting in slightly inaccurate colors. Delicate structures such as wires, fine text, or patterns tend to be plagued by color bleeding. Performance was more robust in natural scenes and wildlife, where priors on color are definitive, and weaker in indoor or man-made objects where there are many possible plausible colorizations.

VII. CONCLUSION

The designed method illustrates the efficiency of deep learning particularly Convolution Neural Networks (CNNs) that can convert grayscale images to natural color images. The technique takes benefit of the LAB color model, which efficiently separates luminance and color information to use exclusively on predicting the chrominance (A, B) components by conducting it only on those, thus resulting in an improved predictive performance. In addition to more robust colorization the split helps preserve the original exposure the picture and ensures that information are not lost over contrast field. As the trial results suggest, the system produces colorizations that are broadly understandable and plausibly realistic without human intervention. Unlike these other techniques the deep learning method is not heavily influenced by new image contents or styles. This can utilized for applications such as restoration task on old photos, sdigitisation of black and white films for archiving, improvement in the Visualisation of medical imaging and assisting 3D artist to develop digital art. You can also enhance and grow the method by integrating state-of-the-art architectures such as Transformer-based models or Generative Adversarial Networks (GANs) which might rug realism and reduce artifacts. The work contributes to improving the effectiveness, scalability, and reliability of CNN-based automatic image colorization systems that is among popular computer vision and image processing techniques nowadays.

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