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Automated Image Colorization Using Deep Learning

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Abstract

Restoring colors to grayscale images has always been a complex challenge in computer vision because a single shade of gray could represent multiple possible colors. Early rule-based and manual methods often gave lifeless or unrealistic outputs. With the rise of deep learning, however, major improvements have been made using CNNs, transfer learning, and generative models. In this work, we present an Efficient Net-based model for automatic image colorization, trained on the large-scale Places365 dataset. To enhance the richness of colors, we introduce a color rebalancing technique that gives more weight to rarely used hues. While traditional evaluation metrics like Mean Squared Error (MSE) remain common, they fail to capture how humans actually perceive image quality. Our results show that the model produces vibrant and realistic colorizations, highlighting both the progress deep learning has enabled and the challenges that remain. We also suggest future directions such as perceptual evaluation metrics, real-time deployment, and user-guided systems.

Keywords: *Automated colorization; Deep learning; Efficient Net; Image restoration; Transfer learning*

1. Introduction

The colorization of images is an extremely important area of research in computer vision that has faced numerous challenges. While restoring colors of images was previously a manual task or one that functions with heuristics, deep learning has made great leaps in its capability to restore colors in images from grayscale versions, making the process fully automated. There are numerous use cases of automated image restoration, such as in archival image restoration, digital art, video processing, and forensic analysis. Visually appealing and semantically consistent results are now possible due to the change from augmentation-based systems to deep neural networks. (Mourchid et al., 2023; Zabari et al., 2023; Kumar et al., 2021). This paper aims to use transfer learning with EfficientNet to colorize images by learning from grayscale images. The system is meant to be data-driven and scalable, and it should work well for many different types of scenes. The key goals of the paper are to: (i) Build a fully automated system for grayscale image colorization, (ii) Develop an EfficientNet based CNN, (iii) Implement color rebalancing methods, and (iv) Analyze the system with appropriate cost functions as well as user studies. The influence of a single color on the human mind and cognition is remarkable, affecting memory, perception, and interpretation. Countless historical photos, surveillance footage, and medical images exist in black and white and therefore lack descriptive aesthetics. Imagine the value that plausible colors (image colorization) can add; this idea has earned considerable attention in research. Heuristic rules and manual artists have in the past attempted to and succeeded in colorization but the outcome is always subjective in addition to costing a lot of time. In large datasets containing images, Convolutional Neural Networks (CNNs) of deep learning are excelling. Their performance on attempting to predict chrominance from luminance using CNN methods greatly improved the field; however, the results were often inconsistent or desaturated. Newer models that include Generative Adversarial Networks (GANs), Transformers, and Diffusion models not only elevate the quality but also make the results semantically relevant. For example, the use of GANs made the textures more realistic, and

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the use of transformers enabled capturing of long-range dependencies that improved context-aware color prediction. (Mourchid et al., 2023; Zabari et al., 2023; Saharia et al., 2022). [1-3]

2. Method

The proposed methodology leverages modern deep learning techniques, specifically transfer learning and color space transformation, to automate image colorization. The system follows an encoder–decoder architecture:

- **Encoder:** EfficientNet-B0 pretrained on ImageNet extracts deep semantic features from grayscale inputs. (Ambadkar & Bhatt, 2023). [4-6]
- **Decoder:** A CNN-based upsampling module predicts chrominance channels (a*, b*) in the CIE Lab color space. (Du et al., 2024).
- **Color Space:** Input L* (luminance) is preserved, while predicted a* and b* channels are recombined to produce RGB outputs.
- **Dataset:** Places365 (scene-centric dataset) converted to CIE Lab color space. (Du et al., 2024).
- **Training Setup:** 100 epochs, batch size 32, Adam optimizer, learning rate 0.001 with decay. [7-10]
- **Loss Functions:** Mean Squared Error (MSE) for pixel-wise accuracy.
- Color rebalancing loss to enhance underrepresented hues.
- **Tools & Frameworks:** Python, PyTorch/TensorFlow, OpenCV, NumPy, Matplotlib. Jupyter Notebook and Google Colab were used for experimentation.

This architecture ensures efficient training, scalability, and extensibility to advanced modules such as attention mechanisms or real-time video colorization in future work. Table 1 shows Summary of System Components

2.1. Datasets

For training and evaluation, we used the Places365 dataset, which contains over 1.8 million images across 365 scene categories. [11-13]

Preprocessing Steps:

Images converted to CIE Lab color space.

L* channel used as input; a* and b* channels predicted by the model.

Normalization: L* → [0,1]; a*, b* → [-1,1].

Images resized to 224–256 pixels.

Data augmentation: horizontal flips, rotations, and crops.

Dataset Split:

Training: ~1.8M images

Validation: ~36.5K images

Testing: ~328K images (Du et al., 2024).

Table 1 Summary of System Components

Component	Description
Goal	Automate image colorization using deep learning
Architecture	EfficientNet + CNN decoder
Color Space Used	CIE Lab
Loss Function	MSE + Color Rebalancing
Tools	Python, PyTorch/TensorFlow
Dataset	Places365

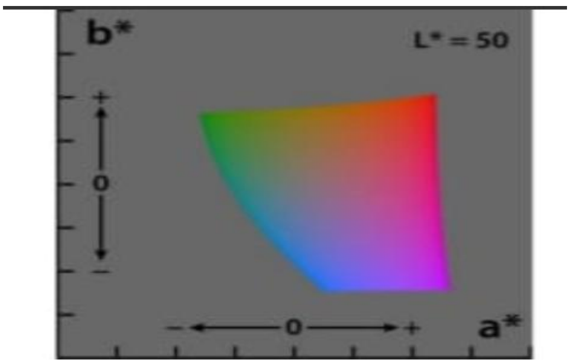

Figure 1 Colors in CIE Lab Color Space When L*=50

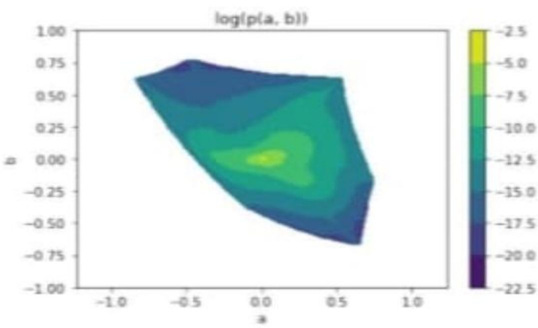

Figure 2 Possibility of Color Appearance in Training Set

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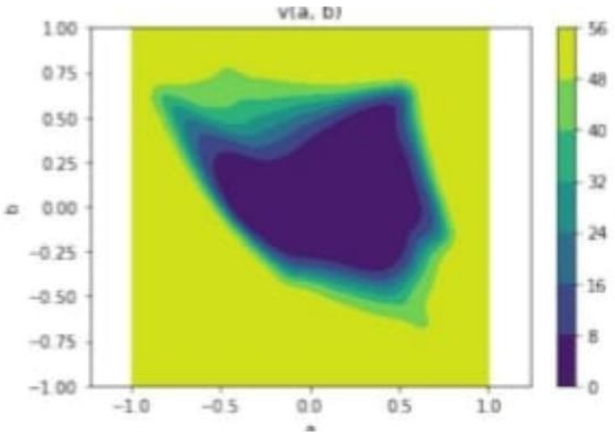

Figure 3 **Adjusted Weight of Each Color When λ=0.9**

3. Results And Discussion

3.1.Results

One of the key deliverables of this project is a deep learning model that can produce colorizations of grayscale images that look natural and are content-wise appropriate, without any manual intervention. With the semantic feature extraction capabilities of EfficientNet coupled with the color rebalancing loss function, the model should successfully address the issues faced by baseline CNNs — including muted colors, lack of variety, and inadequate generalization.

3.1.1. Quantitative Results

- Decrease in Mean Squared Error (MSE) over standard CNN models.
- Greater consistency during the training process as a result of EfficientNet's pretrained weight initialization.

3.1.2. Qualitative Results

- Alongside an overall boost in the vibrancy of the resulting colors, an increase also in the variety of tones, with special attention to preserve the dull shades where earlier models tended to oversimplify.
- More rigid semantic accuracy, with appropriate colorization applied to object classes such as sky, vegetation, and roads that corresponds to real-world human perception.
- Scratch and edge details preserved with fidelity as a result of skip connections in the decoder.

3.2.Discussion

The proposed method has the specific objective to tackle the problems in the following aspects of colorization methods:

3.2.1. Color Diversity and Realism

Old methods consistently generate "safe" colors—e.g., brown, gray, and other muted shades. In our model, we combine color rebalancing loss, which not only encourages the generation of infrequent colors but also enhances overall color diversity. As a result, the outputs are more vibrant and true-to-life (Shafiq & Lee, 2024;Kim et al., 2022). [14]

3.2.2. Perceptual Quality vs. Quantitative Metrics

Although MSE is an algorithmic metric, it has the same score for very different images. Such examples strongly argue for the use of perceptual evaluation metrics, e.g., SSIM (Structural Similarity) or LPIPS (Learned Perceptual Image Patch Similarity), in the next phases. (Weng et al., 2022).

3.2.3. Generalization Across Domains

Since the model is trained on a large and diverse dataset (Places365), it is expected to perform well across a wide range of categories including landscapes, urban environments, and human-centered scenes. However, specialized domains like medical imaging or historical photographs may still present challenges, requiring domain adaptation or fine-tuning. (Lee et al., 2022). [15]

3.2.4. Computational Efficiency

One of the distinguishing strengths of our approach is the EfficientNet encoder, which balances accuracy and computational cost. This makes the model suitable not only for academic exploration but also for practical deployment on edge devices with limited computational resources

Figure 2 **Example of Input of Grayscale Images and Output from Model**

Conclusion

This work demonstrates that combining EfficientNet encoders with color rebalancing leads to vibrant and realistic image colorizations. While numerical metrics like MSE don't always reflect visual quality, qualitative assessments show clear improvements in realism and diversity.

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