UDC 621.391

IMPACT OF COLOR SPACE ON NEURAL NETWORKS

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Received April 4, 2025

Abstract. The choice of color space can significantly affect the performance and interpretability of neural networks in image-based tasks, but its impact remains underexplored in many deep learning applications. This study investigates how different color representations (such as RGB, HSV, LAB, and YCbCr) affect the accuracy and convergence speed of convolutional neural networks (CNNs). Through systematic experiments on benchmark datasets, we evaluate the effectiveness of these color spaces in classification and semantic segmentation tasks. Experimental results show that when using single color space on tasks like classification and semantic segmentation, traditional RGB still has its advantages.

Keywords: color space, neural network, ResNet, U-Net

Introduction

Color is a fundamental aspect of visual data, yet the choice of color representation in neural networks is often overlooked, with RGB being the default in most frameworks. However, different color spaces encode information in different ways–giving priority to brightness, chromaticity, or perceptual uniformity–which can significantly affect model performance [1]. While convolutional neural networks (CNNs) excel on image tasks such as classification and segmentation, their sensitivity to illumination variations, noise, and texture details raises questions about whether alternative color spaces (e.g., HSV, LAB, YCbCr) can improve robustness or efficiency. Existing work has mainly focused on architectural innovations, while the role of color spaces has been understudied. In this paper, we systematically evaluate the impact of RGB, HSV, LAB, and YCbCr on the performance of CNNs in tasks such as object detection and segmentation. Through experiments on benchmark datasets, we analyze the accuracy, convergence speed, and generalization ability under different conditions.

Color spaces are mathematical models that define how colors are represented numerically, each emphasizing distinct aspects of color perception (e.g., brightness, contrast, or hue) [2]. The choice of color space directly shapes how neural networks extract and interpret visual features, as different representations highlight or obscure patterns in images [3]. For instance, a space that isolates brightness might simplify tasks in varying lighting conditions, while one preserving color relationships could enhance object recognition.

RGB is the most popular color space being used. It is typically implemented using 24-bit representation, with 8 bits allocated to each of the R (Red), G (Green), and B (Blue) channels. This configuration yields a value range of 0 to 255 per channel per pixel. This color space is based on the principle that all colors can be represented through mixing varying intensities of red, green, and blue.

HSV (Hue, Saturation, Value) is a perceptually oriented color space designed to align with human visual perception. It parameterizes color information in three dimensions: hue (spectral color), saturation (color purity), and value (brightness intensity). The hue component spans a circular range from 0° to 360°, while saturation and value are quantized in the range of 0 to 255.

The CIE LAB color space is a device-independent model designed to reflect human vision. It separates lightness (L) from color components (A for green–red, B for blue–yellow), making it useful for accurate color comparison, correction, and analysis across applications. To convert from RGB to LAB, the process involves two main steps: first convert RGB to XYZ, then XYZ to LAB [4].

YUV, YCbCr, and YPbPr are complementary color spaces. They have a luma channel and two chroma channels, represented in a complementary fashion (usually red to green, blue to yellow). YUV, YPbPr, and YCbCr are color spaces commonly used for television transmission. YCbCr is commonly used to encode digital color information in video and still image transmission and compression technologies such as JPEG and MPEG.

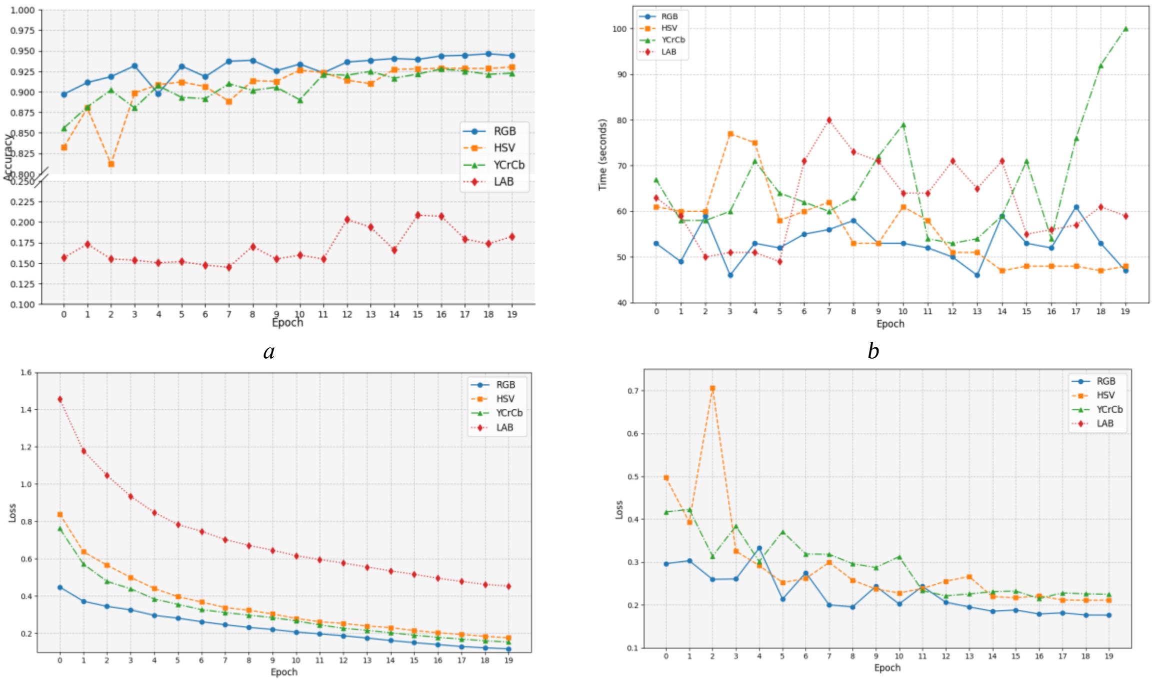
Experiments and Results

In this study, we conducted empirical experiments on two different tasks to evaluate the impact of color space choice on computer vision performance: image classification and semantic segmentation. Four popular color spaces widely used in the field of computer vision and their impact on neural network performance were studied: RGB, HSV, LAB, and YCbCr. Performance was evaluated through two quantitative metrics:

1. Task-specific accuracy (classification accuracy and segmentation Dice score).
2. Computational efficiency during training (epoch convergence rate, epoch time consume).

For the classification task, we employed a pretrained ResNet-18 convolutional neural network (CNN) with transfer learning, then fine-tuning the model on the Intel Image Classification benchmark dataset. We've tested RGB, HSV, LAB, YCbCr on this model.

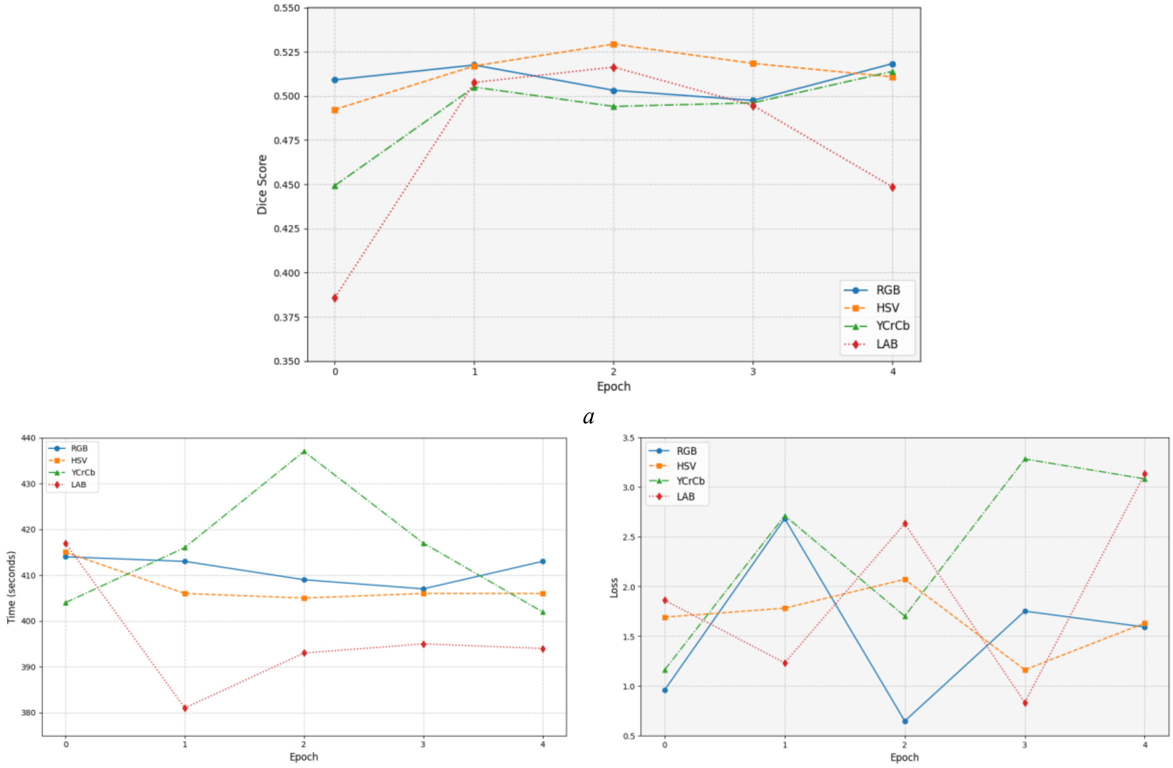
As illustrated in Figure 1 plot (*a*), the results demonstrate that RGB achieved the highest accuracy (94,4 %), outperforming HSV (93,0 %) and YCrCb (92,8 %). In contrast, LAB lagged significantly with the lowest accuracy (20,8 %). The analysis also reveals that the choice of color space impacts computational efficiency during training as shown in plot (*b*): datasets trained with RGB required the shortest average epoch time, while LAB incurred the longest training time per epoch. YCrCb and HSV exhibited nearly identical epoch times, though YCrCb showed greater variability across training iterations. Furthermore, plots (*c*) and (*d*) in Figure 1 indicate comparable convergence speeds across all color spaces. However, the validation loss for LAB diverged markedly from the others, exceeding the plot's scale, which underscores its poor performance relative to RGB, HSV, and YCrCb.



a *b* *c* *d*

Figure 1. Comparison across color spaces by each epoch of classification task:
a – accuracy; *b* – time consume; *c* – train loss; *d* – validation loss

For segmentation, we employed the U-Net architecture using a publicly available PyTorch framework and trained it on the Dynamic Earth Net dataset [5], which provides high-resolution multi-spectrum satellite imagery with multi-class annotations. As shown in Figure 2 plot (*a*), RGB achieved the highest Dice score (0,518), closely followed by YCrCb (0,514) and HSV (0,511), while LAB performed significantly worse (0,449). The experiment also highlights the impact of color space on training efficiency. Plot (*b*) reveals that RGB and HSV inputs required nearly identical epoch times, whereas LAB trained the fastest and YCrCb was the slowest. Notably, YCrCb exhibited greater variability in epoch duration across iterations. Plot (*c*) further demonstrates disparities in convergence behavior: LAB and YCrCb inputs struggled to converge, while RGB and HSV showed similar convergence speeds.



a

b *c*

Figure 2. Comparison across color spaces by each epoch of semantic segmentation task:
a – dice score; *b* – time consume; *c* – train loss

The analysis of color spaces in classification and semantic segmentation tasks reveals the performance and efficiency trade-offs. For classification, RGB consistently provides superior accuracy and computational efficiency (shortest epoch time), while LAB exhibits significantly worse accuracy and longer training time, with a completely different validation loss. Similarly, in segmentation, RGB achieves the highest Dice score, outperforming HSV and YCrCb, while LAB again lags behind. Notably, LAB exhibits inconsistent computational behavior: it trains fastest for segmentation but slowest for classification, suggesting task-related efficiency differences. In both tasks, YCrCb exhibits high epoch time variability and convergence challenges, especially in segmentation. While HSV strikes a balance between moderate accuracy and stable training time, RGB emerges as the most reliable choice overall, combining strong performance, efficient training, and consistent convergence. These findings highlight the importance of color space choice in improving accuracy and computational resource allocation for specific tasks.

Conclusion

This study evaluates the performance of RGB, HSV, LAB, and YCbCr color spaces for CNN-based image classification and segmentation. Experiments on ResNet-18 and U-Net architectures show that RGB consistently outperforms other options when using only one color space, achieving the highest accuracy (94,4 %) and Dice score (0,518) through efficient training. LAB exhibits task-dependent inefficiencies (slowest for classification, fastest for segmentation) and poor accuracy, while YCrCb exhibits unstable convergence and variable training time. HSV balances moderate performance and stability, but lags behind RGB.

The results highlight the robustness of RGB as the default choice for most tasks, likely due to the architectural optimization of neural networks for raw pixel correlation. LAB or HSV may be suitable for niche scenarios where computational speed (segmentation) or illumination invariance is prioritized. Future work should explore hybrid representations or domain-specific adaptation. This work highlights color space as a critical but overlooked hyperparameter for optimizing vision models.

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