Color Matters: Evaluating the Role of Color Space Modeling and Color Analysis in Biomedical Image Interpretation Using Machine Learning

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Abstract. Biomedical image analysis has traditionally relied on grayscale or minimally processed RGB inputs for machine learning (ML) and deep learning (DL) models. However, this assumption often overlooks the diagnostic significance embedded in color variations, which can carry critical structural and pathological information. This work systematically investigates the role of color space transformations, channel selection, and color-aware preprocessing techniques—including local normalization, histogram matching, and chromatic feature extraction—across multiple biomedical imaging tasks.

Experiments span across seven distinct projects involving MR brain imaging, retinal vessel segmentation, dermoscopic lesion classification, blood cell synthesis, and chemical solution analysis. Findings reveal that selecting appropriate color spaces (e.g., HSV, CIELAB, YUV) and channels (e.g., green from RGB, Y from YUV) can significantly improve segmentation accuracy (up to +8% Dice), classification recall (up to +0.38), and regression precision ($R^2 > 0.999$). Further, integrating color histograms into GAN training improves realism and performance in synthetic image generation.

This work provides empirical evidence that color is not merely a visual aid but a quantifiable, discriminative feature that, when modeled correctly, enhances ML/DL performance across biomedical imaging modalities. The study highlights the necessity of color-aware design choices in future computer-aided diagnosis systems.

1 Introduction

Machine learning has become fundamental in biomedical imaging, powering tools for segmentation, classification, and data augmentation. Yet, many systems still default to grayscale or raw RGB representations, often ignoring the rich diagnostic value inherent in color cues. In various clinical contexts—such as retinal imaging, dermoscopy, and histopathology—color can reflect physiological conditions, disease progression, or imaging artifacts.

This work explores the hypothesis that informed use of *color space modeling* and *color analysis* significantly improves ML and DL outcomes. My research spans multiple imaging modalities and tasks, linked by a unifying goal: to make color-aware design a core component of biomedical image interpretation pipelines.

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2 Research Questions

Among others, I investigate the following key questions:

- **RQ1:** How do color space transformations (e.g., HSV, CIELAB, YUV) impact segmentation and classification performance across modalities?
- **RQ2:** Does domain-specific channel selection yield better performance than standard RGB or grayscale approaches?
- **RQ3:** Can color-aware preprocessing (e.g., local normalization, histogram matching) improve robustness under variable imaging conditions?
- **RQ4:** Does incorporating color features into loss functions improve GAN-based biomedical image synthesis?

3 Completed Contributions

My study draws from seven focused projects across different biomedical imaging modalities. These are summarized visually in Figure 1, which illustrates the dataset domains, tasks (segmentation, classification, regression, synthesis), and associated color-aware techniques used.

3.1 Color-Aware Segmentation and Classification

In retinal vessel segmentation, the Y channel from YUV color space achieved the highest average Dice score (0.879), outperforming grayscale (0.835) and other channels such as G (RGB) and L (HLS/CIELab). CLAHE-based contrast enhancement further improved vessel visibility, and when paired with an attention-based U-Net using a hybrid loss function, enabled high-precision segmentation suitable for clinical diagnostics. Similarly, in dermoscopic lesion detection, using the R channel from RGB and S from HSV improved recall by +0.38, highlighting the diagnostic value of chromatic features.

3.2 Thresholding

In MR brain scans, I applied local normalization followed by adaptive thresholding (Sauvola, Otsu, Bernsen) for detecting white matter hypersensitivities. Results showed improved segmentation performance, although parameter sensitivity across patients suggests a need for adaptive tuning. On the other hand, channel-wise analysis

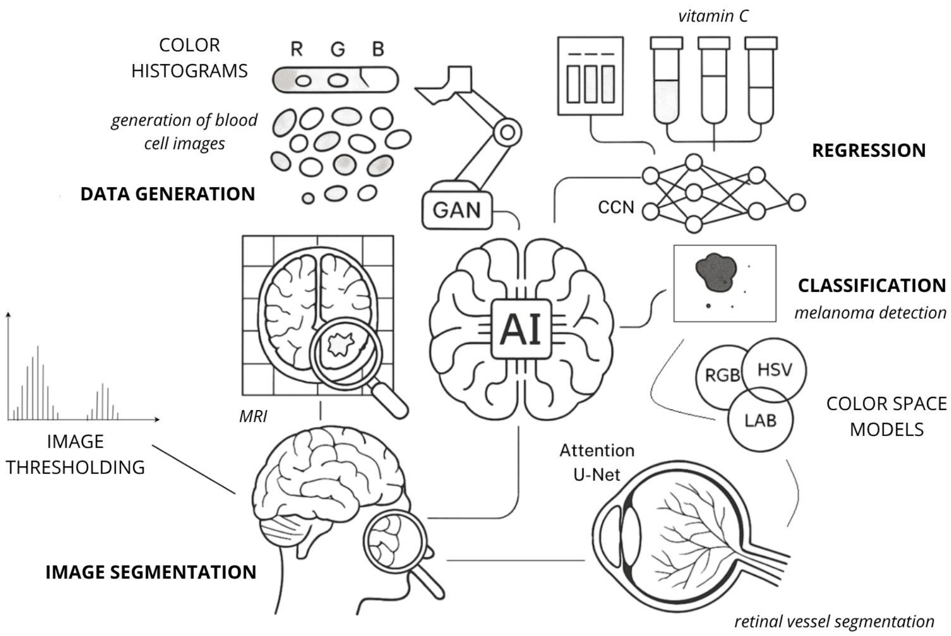

Figure 1. Schematic visual representation of the role of color analysis in biomedical image interpretation with the use of machine learning.

across 19 channels from six color models for retinal vessel extraction revealed that the RGB-Green channel combined with the Moments algorithm achieved the highest Dice (0.7840) and accuracy (0.9599), with luminance-based channels consistently outperforming chrominance ones. These unsupervised methods, enhanced by CLAHE and TopHat preprocessing, offer efficient, training-free alternatives for resource-limited settings.

3.3 Color Standardization for Regression

I proposed a histogram-matching algorithm for standardizing solution images used in vitamin C quantification. When integrated into a regression pipeline, it produced neural network predictions with $R^2 > 0.999$, demonstrating that color consistency significantly enhances analytical accuracy.

3.4 GAN-Based Data Synthesis

A Mixture-of-Experts conditional GAN (MoE-cGAN) was developed to generate synthetic blood cell images. By incorporating red and green histogram-based loss functions, the GAN improved image realism and boosted downstream classification accuracy to 97%.

4 Novelty and Technical Insights

The novelty of this work lies in:

- **Cross-domain chromatic benchmarking** — systematic evaluation across retinal, dermoscopic, chemical, and MR imaging tasks.
- **Channel-aware deep learning** — attention mechanisms and architectural choices informed by color signal strength.
- **Color-informed preprocessing** — applying histogram normalization and color-guided thresholding in clinical contexts.
- **Color-guided loss functions** — improving GAN performance with chromatic consistency constraints.

These findings support the thesis that color is not a secondary visual cue, but a *first-class feature* for machine learning in biomedical applications.

5 Future Work

I am currently exploring:

- Automated color space and channel selection using reinforcement learning to optimize model inputs per task and modality.
- Color explainability studies to identify which chromatic features models rely on most and how they correlate with known pathology.
- How the combination of various channels from different color space models can influence segmentation and classification outcomes.
- Dynamic preprocessing pipelines that adapt contrast enhancement and normalization strategies based on input color distribution.

6 Conclusion

This work demonstrates that color modeling—when thoughtfully integrated—enhances biomedical image analysis across tasks and modalities. My multi-project approach shows that color-aware machine learning is not only viable but necessary for robust, generalizable, and clinically useful diagnostic tools.

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