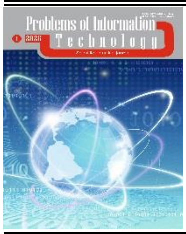

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Qualitative analysis of medical image colorization with the realistic color palette adjustment

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ABSTRACT

Historically, radiological images have been predominantly represented in grayscale, largely due to hardware constraints and the intrinsic characteristics of the imaging process. As a result, physical parameters are typically mapped to a single-channel intensity representation, which has become the standard format for both academic analysis and publication. In this paper, we examine image colorization methods and techniques aimed at enriching radiological imagery with additional information beyond organ texture alone. The proposed methodology not only applies existing colorization approaches, but also systematically investigates color palettes that may be semantically meaningful for the target medical domain. To develop realistic and domain-relevant color palettes, we analyze color distributions in various medical images derived from surgical content. The outcomes of colorization using different palettes are qualitatively evaluated with respect to their impact on image segmentation. The developed visualization software and experimental code are publicly available at: https://github.com/ADA-CompVision/ImageColorization.git

1. Introduction

Radiological images have been captured on grayscale since their emergence tied to the evolution of all images, due to the limitations of the hardware and storage. Starting from the 1950s, radiograms found its definition and started evolving. Despite the overwhelming improvements that they got ever since, the fact that radiological images were grayscale stayed unchanged. Over the course of its existence, grayscale became the norm for algorithmic pipelines, and in general academic publications. Consequently, this brings out its own shortcomings with the lack of color in the images.

In this paper, we experiment with various methods of classical colorization techniques to analyze the efficiency of their use in radiological diagnosis. In parallel, we conduct experiments on color palettes derived from real photographic medical images in order to identify color mappings that are applicable and meaningful for radiological colorization.

Classical colorization methods primarily emphasize the process of assigning color, rather than the semantic relevance of the chosen colors themselves. This limitation is particularly problematic in the medical domain, where specific color ranges and shades can carry critical interpretive significance. An inappropriate or arbitrary choice of colors may therefore obscure clinically relevant details or lead to misleading interpretations.

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The objective of this work is to support medical professionals by exploring colorization strategies that are both technically effective and semantically informed. By combining the evaluation of colorization techniques with a systematic analysis of medically relevant color palettes, this study proposes a new perspective on enhancing radiological scans beyond traditional grayscale representations.

2. Related work

There are many approaches to image coloring; one of them is seeing it as an optimization problem where nearby pixels should have similar Red, Green, and Blue (RGB) values (Levin et al., 2004). However, this method requires manual input from the user, making it not universally applicable.

With the development of medical technology and advances in the hardware, colorization for 3D images gained interest. Mathur et al. (2021) propose a model that generates color hints from style transferring on 2D samples and applies that information on 3D images. Colorization methods, based on generative adversarial network (GAN), create artifacts in images. Zhang et al. (2022) find that the issue stems from adversarial training used in GAN models' development. The suggested solution applies a spatial mask to eliminate the additional noise by creating a distinction between objects and backgrounds in the training images. Based on the CycleGAN Liang et al. (2022) develop a technique that learns from unpaired datasets of gray and colored images. For better image quality, the perceptual loss function and the total variation (TV) loss function are utilized in this method. Theophilus Nathanael and Prasetyo (2024) apply U-net network as an image processing architecture basis. Researchers' approach differs in that it combines U-Net with attention modules and classification embeddings. This structure provides a network with better semantic information leading to improvement in filtering and loss functions' results. Chen et al. (2023) develop an edge-loss function and multi-modal discriminator to address the color bleeding problem often present in colorization methods. The obtained model creates semantically correct and consistently colored images with preserved textures. Researchers implement a cycle between two networks, the first containing Gray MR images and the second built on RGB Anatomy datasets. The essential components of Chen et al.'s (2023) system are a 6-layer encoder-decoder generator, a segmentation network, and a discriminator. There, the generator creates three-channel-colored images from the greyscale samples, and the segmentation network constructs feature maps, while the discriminator categorizes real samples from produced. In addition to previously mentioned elements, an attention-guided generator is applied for better feature extraction via edge semantic information.

3. Colorization techniques

Classical (non–deep learning) colorization approaches are still widely used in medical imaging as visualization tools, mainly because they are deterministic, fast, and do not require training data. However, unlike true-color modalities (such as endoscopy), most radiological scans are inherently scalar-valued (intensity/density/echo strength), meaning that any added color is typically "false color"—useful for perception and communication, but not a direct physical measurement. For this reason, the literature often emphasizes that medical pseudocolor should be applied conservatively and with attention to perceptual side effects (e.g., artificial boundaries, misleading saliency, or distorted contrast) (Rogowitz & Treinish, 1998; Levkowitz & Herman, 1992).

A common baseline technique is pseudo-coloring via a lookup table, where each grayscale intensity is mapped to an RGB triplet using a predefined color scale (Gonzalez & Woods, 2018; NEMA, n.d.). This idea appears throughout image-processing literature under gray-level color transformations (including continuous colormaps and variants of intensity slicing) (Gonzalez & Woods, 2018). In medical contexts, LUT-style pseudocolor is also formalized in standards and workflows: for example, DICOM defines mechanisms for storing and sharing palettes and even provides "well-known" palettes (often used in nuclear medicine/PET) intended to make intensity differences more visible to human observers (NEMA, n.d.). At the same time, visualization research repeatedly warns that certain popular maps (especially rainbow-style palettes) can introduce non-uniform perception and false edges, so perceptually informed color scales are strongly recommended when interpretability matters (Levkowitz & Herman, 1992; Rogowitz & Treinish, 1998; Borland & Taylor, 2007).

Band (or range-based) colorization is a more discrete version of LUT mapping. Instead of a smooth color transition, the grayscale axis is divided into a small number of intensity intervals ("bands"), and each band is assigned a single representative color (Gonzalez & Woods, 2018). This family of methods is often described as intensity-level slicing, and it is typically used when the goal is to highlight specific value ranges (e.g., emphasizing certain density/brightness intervals) rather than preserving fine continuous gradients (Gonzalez & Woods, 2018). The main trade-off noted in the literature is that while banding can make category-like differences easy to spot, it can also erase subtle within-band variations and create artificially sharp boundaries that do not exist in the original image (Gonzalez & Woods, 2018; Levkowitz & Herman, 1992). Another classical route is to first partition the image into groups using k-means clustering and then assign a distinct color to each cluster. K-means itself originates from early clustering work and is closely connected to least-squares quantization ideas (i.e., representing data with a limited set of prototypes) (MacQueen, 1967; Lloyd, 1982).

In imaging, k-means is frequently used as a lightweight segmentation/quantization baseline: pixels can be clustered by intensity alone (or by feature vectors that include texture or spatial cues), after which clusters are rendered with separate colors to visually separate major regions (MacQueen, 1967; Lloyd, 1982; Pham, Xu, & Prince, 2000). Medical image segmentation surveys discuss clustering methods (including k-means and related fuzzy variants) as practical tools that can be effective for coarse partitioning, but may struggle when boundaries are weak, noise is strong, or tissue classes overlap in intensity distributions (Pham, Xu, & Prince, 2000). As a result, k-means colorization is often best interpreted as a "segmentation-style visualization" rather than a faithful enhancement of continuous diagnostic texture (Pham, Xu, & Prince, 2000).

Unlike LUT and clustering approaches that operate directly on intensity, example-based color transfer methods aim to "borrow" a color style from a separate source image. A widely cited baseline is the Reinhard color transfer method, which converts images to a perceptually motivated color space (commonly CIE L*a*b*) and then matches simple statistics (mean and standard deviation) of channels between a source (reference) and target image (Reinhard et al., 2001; ISO, 2019). Because CIE L*a*b* is designed so that Euclidean differences better approximate perceived color differences than raw RGB, it is commonly used in color transfer and color difference computations (ISO, 2019). Later work generalizes the same goal—matching source and target color distributions—through more flexible histogram or probability density transfer techniques, which can better align complex color distributions than simple moment matching (Pitié, Kokaram, & Dahyot, 2005). In medical visualization, the key limitation is conceptual: unless the reference image is clinically meaningful, the resulting "natural-looking" palette can still be semantically arbitrary (visually plausible but not anatomically grounded) (Reinhard et al., 2001; Pitié, Kokaram, & Dahyot, 2005).

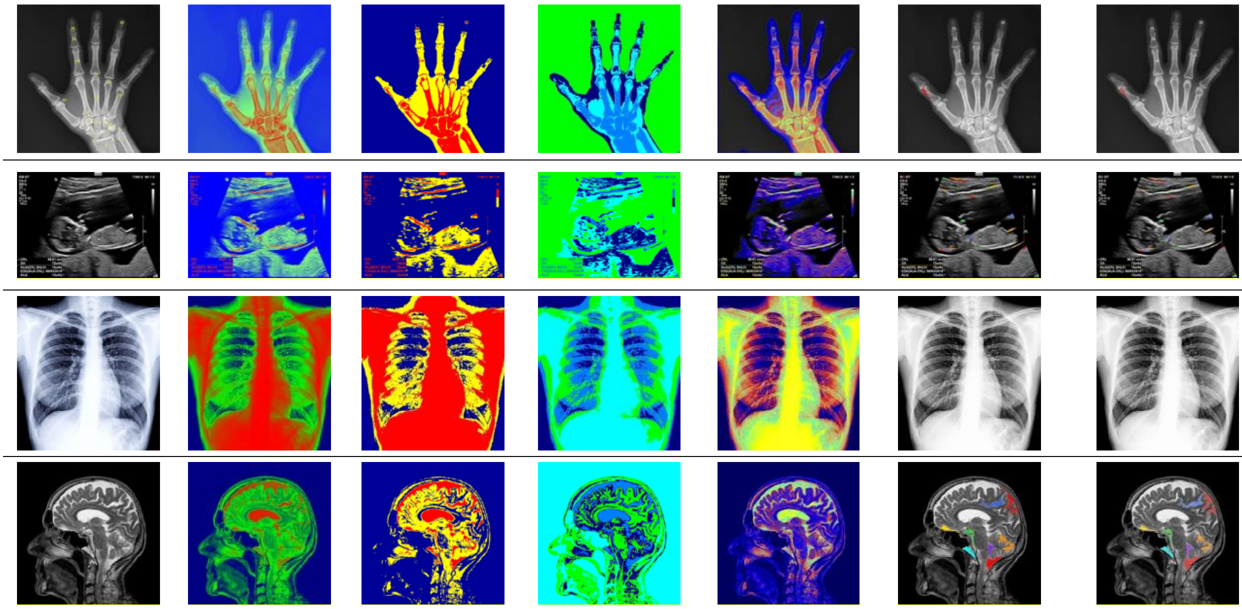
A final family of classical techniques is region-based visualization, where the image is first decomposed into regions (for example, via connected components on a mask, region labeling, or other segmentation outputs), and then color is applied at the region level. Connected component labeling is a foundational operation in digital image analysis and underlies many region-based pipelines used to isolate structures before visualization (Rosenfeld & Pfaltz, 1966). Once regions are available, they can be shown with solid colors or displayed using blended overlays so that the original luminance/texture remains visible. Blending is commonly described through alpha compositing models, where a transparency term controls how strongly the overlay color mixes with the original image—an idea formalized in classic compositing work (Porter & Duff, 1984). In practice, the region-based family is often considered the most "conservative" for medical images because it can localize color only to selected structures and avoid recoloring the entire scan, which supports attention guidance while preserving the original diagnostic cues (Pham, Xu, & Prince, 2000; Porter & Duff, 1984).

4. Experiments

This section describes the proposed approach, includes the methods of colorization and describes the software for visualizing the achieved results. Inputs are various types of grayscale medical images, each taken and processed separately with Python.

Table 1. Description of the colorization techniques on different medical image types

Original photo	Pseudo-Color LUT	Band Colorization	K-means Colorization	Reinhard Color Transfer	Region based coloring with solid colors	Region-based color blending



OpenCV and NumPy documentation was used in the implementations details of color-space conversion, datatype handling, colormaps, clustering utilities, connected components, and alpha blending (OpenCV Developers, 2023; Harris et al., 2020).

Input is grayscale and in case input is Red Green Blue (RGB), it is converted to Grayscale. Afterwards, all inputs are clipped into the uint8(8-bit unsigned integer) format to make it compatible with all OpenCV operations. Then, floating point conversion using NumPy is applied to bring the range from 0-255 to 0-1. This conversion is to prevent distortions caused by per-image contrast (Gonzalez & Woods, 2018). After pre-processing steps, input undergoes a range of different colorization techniques. Each colorization technique is implemented in a deterministic and modular way without interfering with each other.

Table 1 depicts the effect of each colorization technique, for different medical image types. Pseudo Color Lookup Table (LUT) colorizes images without changing underlying data using predefined mapping. LUT additionally, uses smooth interpolation which fills in-between defined points with color ; consequently, avoids sharp jumps (Gonzalez & Woods, 2018). LUT methods change the way mapping happens. In this technique, interpolation is used among LUT entries. Based on intensity of the entries, colors are transformed by the lookup table. As a result, LUT technique makes small jumps easier to observe without changing the original data (Gonzalez & Woods, 2018).

The second method that was examined was Band-based colorization (Gonzalez & Woods, 2018). In this method, grayscale intensities are grouped into three distinct categories. Afterwards, each were mapped onto different RGB colors (Gonzalez & Woods, 2018). Unlike the previous method , LUT, Band-based colorization creates sharp differences between set RGB colors. Different grayscale intensities within the same category are mapped to a single RGB color in the colorized image. Therefore, discrete intensity values that fall within the same category become indistinguishable in the output (Gonzalez & Woods, 2018).

Next method on the list is K-means intensity Clustering. This colorization method uses K-means clustering directly on the image, mapping it onto predefined palette, creating region-aware colorization without considering nearby regions' colors. To further explain this, the grayscale pixels are categorized based on their intensities into k groups without spatial smoothing. Therefore, output does not contain a spatial context or learned features.

The following colorization method - the Reinhard Color Transfer is a commonly used classical colorization method. This technique utilizes converted image's LAB channels, which stands for L as in light, A as in green-red, and B as in blue-yellow (Reinhard et al., 2001). These LAB means and standard deviations are used to determine color distribution of final output (Reinhard et al., 2001). Light ranges from 0 to 255, which accordingly, equals pitch black to light. A and B respectively match its positive values to red/yellow and negative values to green/blue (ISO, 2019).

Region based coloring with solid colors technique tends to work with distinct regions of the grayscale image. These regions are identified and isolated based on the intensities of binarized values. Same or similar values are categorized, which afterwards, are segmented as candidate regions. Remaining byproduct parts of the image are discarded and considered noise.

As a result, Region based coloring with solid colors method may become useful for medical images that need to point out prominent regions that can showcase details which otherwise would have been missed. Finally, each selected dominant part of the image is colored uniformly as output (Gonzalez & Woods, 2018).

An alternative approach of the same method, Region-based color blending displays each section of the colorized version using alpha compositing (Porter & Duff, 1984). To begin with, grayscale is segmented based on its connectivity and intensity. Later, each of region is treated separately. Following, a target color is assigned to each region and blended with the underlying grayscale using an opacity parameter α. In practice, α controls how strongly the assigned color shows up in the region: an image with lower α is more similar to the original grayscale, while higher α makes the region color more dominant.

Ultimately, the different colorization techniques transform input into a three-channel RGB image that shares the same spatial structure. In contrast to traditional grayscale or undersaturated monotonous medical images, such colorized version of the input is useful to detect, determine, and analyze the possible issues in the images (Zabala-Travers et al., 2015).

To understand the robustness of the grayscale structure after the addition of colors, the original grayscale radiograph of the human hand (see Figure 1) was compared to the luminance channel (L) of each of the colored images in the CIE L*a*b* space. The comparison was achieved using the PSNR and SSIM metrics, which quantify pixel-level intensity deviation and structural similarity in terms of luminance, contrast, and spatial organization, respectively (Wang et al., 2004).

The comparison revealed significant differences in the preservation of the structural topology between the methods, where the lowest structural fidelity was achieved by the K-means method, with a PSNR of 3.43 dB and a corresponding SSIM of 0.22. The band method resulted in a moderate effect on the radiograph, where the PSNR and SSIM values were 13.06 dB and 0.61, respectively, corresponding to a threshold effect on the contrast boundaries. However, the solid blending and Reinhard methods preserved the structure almost perfectly, where the PSNR values were 34.23-50.83 dB and the corresponding SSIM values were 0.99.

These results imply that structural distortion is not an intrinsic consequence of the inclusion of color but depends on the specific transformation technique used. The clustering and threshold methods are used to enhance the saliency of the images, and the topology of the intensity distribution of the radiograph is altered, resulting in the distortion of the structure. The blending methods, on the other hand, are used to add colors to the images, and the topology of the radiograph remains almost the same, and only the colors are changed.

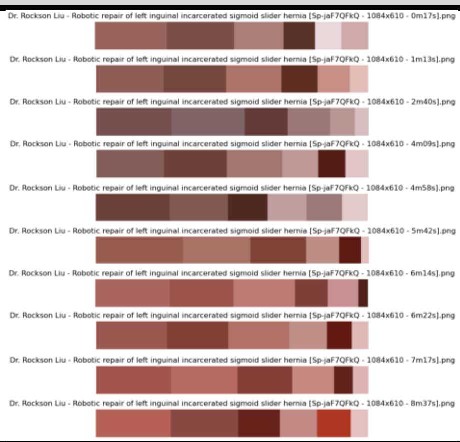
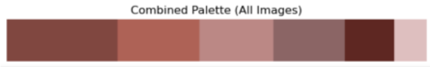
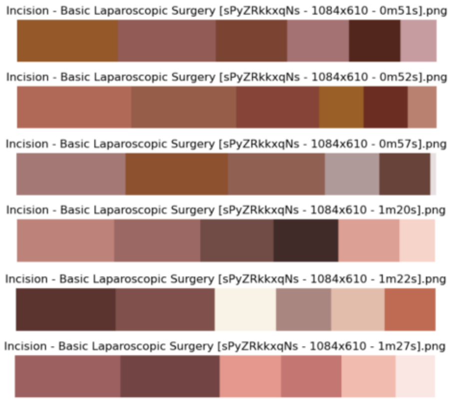
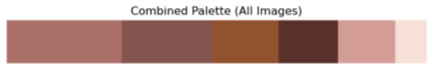
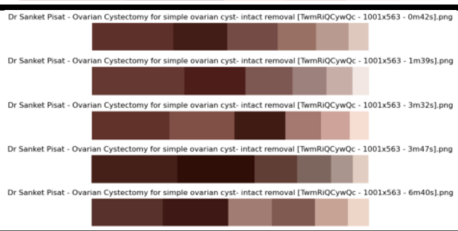
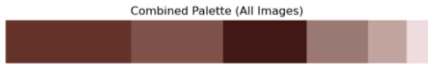
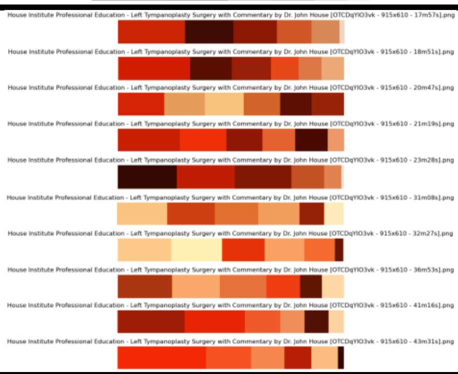
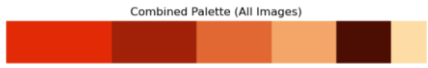
5. Discussion

The outcomes of applying classical colorization methods to four different medical image types are shown in Table 1. To keep the comparison fair, all experiments were run using the same default settings.

In addition, the Reinhard Color Transfer method was tested without providing an extra reference image. We used four medical imaging modalities: hand X-ray, ultrasound, lung CT, and MRI. The purpose of the usage of this modality was to see how robust each method is across different kinds of scans.

Starting with the hand X-ray images, each method tends to emphasize different parts of the hand. The pseudo-color LUT approach does a good job of highlighting density changes while also keeping fine edges sharp.

Table 2. Color palettes observed in different organs taken from the surgery images

Surgery Name	Palette from a single image	Combined Palette
Sigmoid Slider Hernia Repair		
Basic Laparoscopic Surgery		
Ovarian Cystectomy		
Left Tympanoplasty Surgery		

Band colorization makes the bones stand out clearly, but it sacrifices subtle joint and bone-structure details.

Similarly, K-means separates bone and tissue from the background, but it flattens the clinically meaningful texture in the image. In contrast, Reinhard Color Transfer gives a more natural-looking result overall.

When we move to ultrasound images, most methods introduce visible artifacts and generally reduce image quality. Pseudo-color LUT and Reinhard Transfer preserve resolution relatively well, but they can exaggerate details by turning speckle into something that looks more like noise. Band colorization and K-means tend to remove structural detail more noticeably.

Compared to these, region-based methods work better because they keep the original resolution while adding color mainly where structure is actually detected. Overall, ultrasound benefits most from conservative colorization - using color subtly so the image stays interpretable instead of becoming visually distracting.

Looking at the lung CT (chest) scans, the differences between methods are easier to see. The pseudo-color LUT approach makes low- and high-density regions stand out by mapping small grayscale changes into a wider range of colors. Band colorization separates soft tissue from ribs more aggressively, which can hide gradual density variations. K-means also reduces subtle changes, but it still provides a clear, coarse split between major regions. In contrast, region-based methods keep the CT mostly intact and add only small, localized color cues, so they work better when the goal is to guide attention without fully recoloring the scan.

The MRI row shows an even sharper contrast between approaches. Since MRI relies heavily on smooth intensity transitions, methods that force the image into a few categories can look unnatural. Pseudo-color LUT increases visual separation between brain structures, but it may feel artificial because large areas are recolored despite subtle underlying contrast.

Band colorization introduces rigid boundaries and compresses important gradients, while K-means creates block-like regions that can oversimplify tissue variation. Reinhard Color Transfer often looks the most visually “natural,” but without a reference image its colors are not anatomically grounded. For this reason, region-based techniques offer a better balance: solid-color region labeling is useful for clear, discrete highlights, and region-based blending integrates the highlights more smoothly while preserving original luminance and texture.

Overall, Table 1 suggests using each method according to intent: pseudo-color LUT is strongest for emphasizing intensity gradients; band and K-means are more segmentation-like but risk losing fine detail; Reinhard prioritizes a natural-looking palette without guaranteed medical meaning; and region-based methods are the most conservative and interpretation-friendly when preserving the original scan matters.

To have more meaningful color palette that is close to the human tissue, we experimented with using the colors taken from the surgical materials. Despite the smaller range of the colors compared to the regular RGB range, this palette offers colors that the doctors are used to see and excludes the unusual colors that might mislead them during the examination. Table 2 shows the various colors gathered from different surgical domains and provides an information about the palette. Images used for the color statistical analysis are derived from four publicly available YouTube videos documenting surgical procedures in detail (Liu, 2021; Incision, 2021; Pisat, 2019; House, 2021). Most of the analyzed surgeries are performed within the abdominopelvic cavity, including sigmoid slider hernia repair, laparoscopic surgery, and ovarian cystectomy (Liu, 2021; Incision, 2021; Pisat, 2019). Due to the anatomical locations of these procedures, robotic-assisted techniques are employed, which influence the quality of the recorded surgical footage.

An additional issue in image colorization comes from the presence of surgical instruments in the frame, most notably in the tympanoplasty procedure (House, 2021). To grapple with this problem, the frames selected for statistical color analysis were carefully chosen to minimize the influence of robotic equipment and medical instruments.

The use of colors in images that are naturally grayscale in the context of radiology can lead to false positives, where the use of intensity variations can become visually salient patterns (Borland & Taylor, 2007; Rogowitz & Treinish, 1998). In general, noise, speckles, gradual gradients, and minor acquisition artifacts are naturally interpreted using contextual relationships between intensity values in a grayscale image.

However, the use of pseudo-color representations, especially those using threshold or clustering methods, can cause gradual intensity variations to become visually salient patterns, such as boundaries between normal and abnormal regions (Borland & Taylor, 2007). The use of high-contrast colors can also enhance the differences between intensity values, causing visual attention to become disproportionately concentrated on normal regions, which can become more pronounced when using pseudo-color representations (Rogowitz & Treinish, 1998).

The use of colors can also cause the brain to become more associated with abnormal regions, causing the severity of lesions to become exaggerated

(Zabala-Travers et al., 2015). The process of using colors in images and the dependency on the method used to process the images emphasize the use of semantic colorization as a form of visualization rather than a diagnostic truth.

6. Conclusion and future work

In this study, we have systematically explored and qualitatively evaluated classical colorization techniques for medical imaging, comparing their performance across modalities such as X-ray, ultrasound, CT, and MRI. Our findings demonstrate that while methods like pseudo-color LUT and Reinhard color transfer can enhance perceptual clarity, they often lack semantic relevance in a clinical context. Conversely, region-based approaches offer a more conservative and interpretable solution, preserving diagnostic integrity while adding guided visual cues. Importantly, the investigation into realistic color palettes derived from surgical imagery underscores the necessity of domain-specific color design. By aligning color choices with anatomical familiarity, we can reduce cognitive load and prevent misinterpretation, thereby supporting more accurate and efficient diagnostic workflows.

The significance of this work lies in its dual focus on both technical colorization methods and the semantic appropriateness of color itself which is often overlooked in conventional image processing pipelines. As medical imaging continues to evolve, the intentional use of color can transform grayscale scans into richer visual tools without compromising clinical validity.

Future work should extend this framework to other imaging domains such as mammography, brain scans, and dermatological images, where color could highlight subtle pathologies or improve tissue differentiation. Additionally, further development of adaptive and learnable palette-generation models, trained on larger datasets of real surgical and anatomical imagery could automate the selection of clinically meaningful colors. Integrating such palettes into AI-assisted diagnostic systems may enhance both human interpretation and machine analysis, ultimately bridging the gap between visualization and diagnosis in modern medicine.

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